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Policy analytics for environmental sustainability: Household hazardous waste and water impacts of carbon pollution standards

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POLICY ANALYTICS FOR ENVIRONMENTAL SUSTAINABILITY: HOUSEHOLD HAZARDOUS WASTE AND WATER IMPACTS OF CARBON POLLUTION STANDARDS

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Policy Analytics for Environmental Sustainability:
Household Hazardous Waste and
Water Impacts of Carbon Pollution Standards

by

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Abstract

Policy analytics are essential in supporting more informed policy-making in environmental management. This dissertation employs a fusion of machine methods and explanatory empiricism that involves data analytics, math programming, optimization, econometrics, geospatial and spatiotemporal analysis, and other approaches for assessing and evaluating current and future environmental policies.

Essay 1 discusses household informedness and its impact on the collection and recycling of *household hazardous waste* (HHW). Household informedness is the degree to which households have the necessary information to make utility-maximizing decisions about the handling of their waste. Such informedness seems to be influenced by HHW public education and environmental quality information. This essay assesses the effects of household informedness on HHW collection and recycling using public agency data, community surveys, drinking water compliance reports, and census data for California from 2004 to 2012. The results enable the calculation of the elasticity of the output quantities of HHW collected and recycled for differences in household informedness at the county level.

Essay 2 considers the *pro-environmental spatial spillovers*, based on agency actions and waste collection behavior that is occurring in other counties, that represent the influence of HHW-related practices in close-by regions. Using county-level spatio-temporal datasets that consist of economic, demographic, and HHW data in California from 2004 to 2015, I evaluate the impact of grants on the HHW collection

activities using a research design that emphasizes spatial variations and controls for confounding factors. A random effects panel data model with instrumental variables is then developed to measure the effects of HHW grant on HHW collection activities while considering the spatial effects from the influence of the waste collection activities among close-by counties or regions.

Essay 3 assesses transition pathways in electricity generation and their future water impacts using an electricity generation capacity expansion model. Scenarios that do or do not comply with the U.S. Environmental Protection Agency's proposed carbon pollution standards – the New Source Performance Standards and Clean Power Plan – are considered. Using the Electric Reliability Council of Texas region as an illustration, the scenarios with the carbon regulations are shown to have lower water use from the power sector than the continuation of the status quo with more electricity generation from coal than natural gas. This is due to an increase in electricity generation from renewable sources and natural gas combined cycle plants that is influenced by the CO_2 allowance price. Water withdrawal limits affect electricity generation, decreasing it from power plants with once-through cooling, but this will increase water consumption.

These essays demonstrate the use of a variety of data analytics and management science methods that represent advances in policy analytics to overcome the research challenges, such as the data limitations, the uncertainties associated with the analysis of energy futures, and best practices establishing causal estimates in empirical research designs. This dissertation contributes to the growing body of research on policy analytics for environmental sustainability and improves our understanding of how to craft policies that enhance sustainability for the future.

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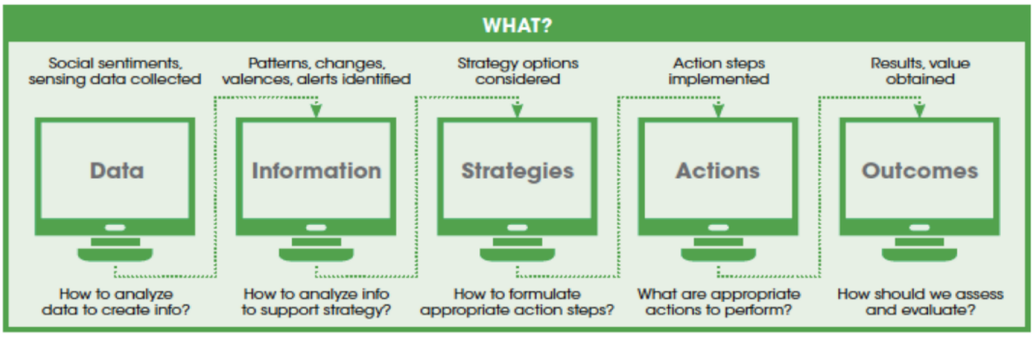
To Kedar and our parents

Chapter 1. Introduction

Climate change, pollution, biodiversity loss, and resource depletion are some of the well-known consequences of human activities (Vitousek et al., 1997) that eventually affect human health, welfare, and quality of life (Callan and Thomas 2013). To address these consequences, policy-makers have an important role in providing effective public policies in achieving environmental sustainability.

Today, new *information technologies* (ITs) enable experts and scientists to collect, store, and analyze data from various sources, including public data sources (government statistics, environmental agencies, weather services, World Bank), firms and organizations (transactions from shipping logs, on sales activities, from click-stream data), and also sensor data (data from thermostats, cameras, satellites, other sensor devices). The data can be analyzed and transformed into meaningful information that is useful for policy-makers to formulate strategies and policies, as shown in the *data and policy analytics framework* below. The framework explains what are transformed and how to transform them from data to information, information to strategies, strategies to actions, and actions to outcomes. (See Figure 1.1.)

Figure 1.1. Data and Policy Analytics Framework (Kauffman 2014)



Policy analytics refers to the development and application of data analytics approaches that "aim to provide meaningful and informative hindsight, insight and foresight" to policy-makers (Tsoukias et al., 2013). It starts from drawing a wide range of existing data and knowledge as in the framework in Figure 1.1. To transform the data into meaningful information, my dissertation uses *fusion analytics.* This combines machine methods from Computer Science and explanatory empiricism, which includes advanced Econometrics and Statistics (Kauffman et al., 2017). This approach increasingly characterizes computational social science, a multidisciplinary field that uses computational approach to social science, in the era of big data (Chang et al., 2014; Kauffman et al., 2017).

Policy analytics is one step ahead of the *evidence-based policy-making* approach that was introduced by the Blair (1994) government to create policies based on the best available evidence from research. Despite the advantages of rational policy-making, the evidence does not guarantee an unambiguous guide to decision-making; in fact, the interpretations of the evidence are subjective and linked to a specific framework (De Marchi, 2014). Policy analytics combines the evidence with approaches to understand individual and social values, culture, and public engagement (Tsoukias et al., 2013).

This dissertation showcases the use of fusion analytics to assess policy analytics issues related to environmental problems. I first focus on the problem of *household hazardous waste* (HHW), which comes from leftover household products containing toxic, flammable, and corrosive material (U.S. EPA, 2014a). If this waste is not properly disposed of, the hazardous materials can contaminate our environment, including groundwater that supplies drinking water. For example, hydrocarbon contaminants may come from motor oils, gasoline, and grease; and heavy metals may come from paints and printing ink (U.S. EPA, 2015a).

Managing HHW requires effective public policies, and also the active participation of citizens. Since not all households are well-informed about HHW and its adverse risks to the environment, *household informedness* is an essential construct that will affect households' decision-making in their consumption, waste generation, and management. It is defined as "the degree to which households have the necessary information to make utility-maximizing decisions in their daily activities" (Lim-Wavde et al., 2016). Essay 1 assesses the role of household informedness in influencing household decisions about the amount of HHW that they enable to be collected and recycled.

The primary research question in this essay is: how has household informedness influenced HHW collection activities in terms of the amount of waste collected? The collected HHW is disposed of in several ways; non-recyclable waste is neutralized, incinerated, and treated in HHW facilities; and some other is recycled and reused. Recycling the waste brings extra revenues to waste managers and saves material resources. Related to this then: how does household informedness affect HHW recycling outputs? And finally: how can the impact of household informedness on HHW collection and recycling output be quantified?

This essay quantifies the effects of household informedness and estimates the responsiveness of informedness on the amount of waste collected and recycled using public data in California. These novel measures are useful for waste managers to gauge the responsiveness of households in terms of the quantity of HHW collected and recycled as more educational programs and environmental quality information become available to them.

Location matters in managing HHW, particularly in regions with cultural and behavioral differences across their geographies. Spatial analysis yields useful insights for different localities. The spatial patterns that are observed may change over time due to the changes in various influential factors. Thus, spatio-temporal analysis of HHW collection may reveal interesting insights that provide useful input for policy-makers to evaluate the management of HHW programs across multiple counties or regions over time. Based on spatiotemporal data in California, Essay 2 assesses the spatial patterns in the HHW collection activities and then measures the causal effect of HHW grants on the waste collection.

This essay first asks: were there key spatial patterns of HHW collection during the study period? Observing the different amount of HHW collected over the years, I also ask: how did they change over time? Among the influential factors of HHW collection activities, this essay focuses on measuring the impact of HHW grants awarded to waste agencies across different counties in different years to improve their HHW facilities and programs. Related to this: how effective was the HHW grant in improving the collection and recycling of HHW? And finally: how do nearby counties impact the HHW collection activity in a county?

By integrating location information in the policy analytics, the research in Essay 2 contributes to policy insights on the spatial patterns in the HHW collection activity in California. It also provides modeling of the causal relationships for HHW grant and spatial effects of HHW collection activities on the amount of HHW collected. The model, along with the analysis that I conduct, is useful in counterfactual impact evaluations that provide a deeper understanding about the effects of HHW grants when location dependency matters in the intended outcomes.

Essay 3 focuses on another important issue: the water impacts of electricity generation. Thermoelectric power plants require a large amount of water for steam generation and cooling purposes. In the U.S., these plants accounted for about 45% of the total water withdrawal in 2010 (Maupin et al., 2014). Changes in regulations and costs in the electric power sector may greatly impact water withdrawal and consumption of power plants. So electricity generation planning should include water impact assessment to manage the water use and to prevent power plant curtailments due to shortage of water.

This essay examines future possible electricity generation pathways: pathways that comply or do not comply with carbon pollution regulations. The overarching research question in this study is: how does each of the pathways affect water use for electricity generation? I also ask: What are the water impacts of complying with the carbon regulations? If retrofitting *carbon capture and storage* (CCS) to existing plants is considered, how will it affect the electricity generation and the water impacts? And finally: how will drought affect electricity generation in the low-carbon pathway?

This essay develops an electricity generation and water assessment framework that contributes to policy insights on the consequences of the carbon-regulation compliant and non-compliant pathways. These insights help policy-makers in selecting the most appropriate pathway.

Each essay contributes fresh insights to policymakers using various analytics approaches. Essay 1 and Essay 2 employ advanced econometric methods for causality and geospatial analytics methods to measure effects of informedness and policies. Essay 3 employs math programming and sensitivity analysis to assess possible future electricity generation pathways and their consequences. The research in these three essays fits the policy analytics research framework that aims to support policymakers in dealing with complex policy decisions in environmental sustainability issues.

The next chapters (Chapter 2, 3, 4) discuss the three essays. Section 5 provides best practice and the essential skills and experience that I obtained during my research. Section 6 concludes with contributions, limitations, and future research.

Chapter 2. Household Informedness and Policy Analytics for Household Hazardous Waste Recycling

2.1. Introduction

Household hazardous waste (HHW) is defined as leftover household products that contain corrosive, toxic, ignitable, or reactive ingredients, such as paints, cleaners, oils, batteries, and pesticides (U.S. EPA, 2014a). Often this waste is disposed of improperly, for example, by pouring it down a household drain, onto the ground, into storm sewers, or simply disposing of them together with the regular trash. If this happens, the waste materials can contaminate the land and infiltrate the groundwater, and consequently create adverse effects on the environment and people's health (U.S. EPA, 2015a). Due to these damaging effects, improving HHW management is essential.

A 2015 review of HHW management performance reported that the amount of HHW collected was only about 0.12% to 1.88% of *municipal solid waste* (MSW) or general trash (Inglezakis and Moustakas, 2015).[1] This amount may not include HHW that is mixed in general trash or disposed of improperly. The diversion of HHW from general trash can be enhanced through various HHW collection programs. The success of these programs depends on household participation in identifying, segregating, storing and transferring HHW to the collection system.

Besides the convenience and effectiveness of HHW collection programs, household informedness is an essential aspect that can encourage household participation. In this study, we define *household informedness*, a construct we first proposed in

[1] The authors derived this from average value data in previous studies on HHW in 20 European countries, several states in the U.S., Mexico, Canada, Greenland, Japan, India, Pakistan, Hong Kong, and Nepal from 1992 to 2013.

an earlier conference presentation (Lim-Wavde et al., 2016), as the degree to which households have the necessary information to make utility-maximizing decisions about the handling of their waste. We focus on household informedness for waste management, though it also is applicable in other disciplines, such as Information Systems (IS), Marketing, Economics, Environmental Management, and Social Science. Research related to informedness has been conducted in other disciplines as well. For example, Shimshack et al. (2007) reported on consumers who received mercury advisories from the U.S. Food and Drug Administration (FDA), and then reduced their canned fish consumption. Li et al. (2014) also showed that informedness about prices and products determined the choices they made. And Byrne et al. (2016) performed an experiment to understand the impacts of different levels of informedness for electricity use related to decision-making for household-level utility maximization. The theories used in these studies are applicable for information policy and waste management for hazardous waste collection, recycling and environmental sustainability.

Household informedness can be influenced through the provision of environmental quality information and public education. Information in the form of notification or alerts about environmental quality can impact household perceptions about the quality of the environment they live in. In HHW public education, people receive information about what types of household materials are hazardous, what alternative non-hazardous products can replace them, and how to properly dispose of hazardous waste (Lund, 2001). This may reduce the generation of hazardous waste, and increase household participation in HHW programs that are provided.

Our study focuses on the effects of household informedness. These effects can be assessed by observing changes in the amount of HHW collected and recycled in the presence of different county and demographic characteristics. However, quantifying the causal effects of household informedness on HHW recycling and collection is not a simple task. The field of waste management has been largely *opaque* because of the complexity of the issues, the diversity of practices among people, firms and local institutions, and the difficulty to observe people's behavior toward their waste (Wijen, 2014). Properly managing waste involves managing heterogeneous stakeholders (households, firms, waste facilities, and local and federal government), as well as other factors (socioeconomic and environmental awareness). Waste reduction relies heavily on people's willingness to participate in reducing, reusing, and recycling their waste, but given the heterogeneity of the stakeholders and variety of factors, there is diversity in behavior and practices.

We selected California for this empirical research because it has diverse county characteristics and accessible annual reporting on HHW collection, disposition, programs, and grant awards. We use data published by California's Department of Resources Recycling and Recovery (CalRecycle), the Annual Compliance Report for Public Water Systems by the California Department of Public Health (CDPH), the American Community Survey, and U.S. census data from 2004 to 2012 for our analysis. The data are observational, not survey-based. Although causal evidence is ideally generated using randomized experiments, randomization is often not feasible in social science settings such as HHW waste management. So causal effect estimates may be hard to establish.[2] To get close to inferring causality, we use econometric approaches that isolate unobservable factors that determine the household

[2] Public education about HHW also may suffer from a possible *policy-related endogeneity* issue. The decision of local government to provide HHW public education may be a purposeful action to meet certain waste collection targets. From our data, we observed that grant awards used for HHW public education programs seemed to be fewer in number when the amount of HHW collected increased. For this problem, we applied an instrumental variable to see if it were possible to address this bias.

informedness variables and explicitly consider all possible confounding factors. Data tests and robustness checks are also performed to confirm the causal relationships.

Our study is based on utility maximization theory. It focuses on waste management decisions at the household level. Previous studies by Kinnaman and Fullerton (2000) and Callan and Thomas (2006) used a similar theory; they also considered disposal unit pricing levels, as discussed by Hong (1999), however, these studies were based on cross-sectional data analysis at the community level. Sidique et. al (2010) used county-level panel data analysis and also discussed the effects of recycling education on the general recycling rate. They also mentioned that the environmental quality which the household perceives may influence the household's utility function. However, this factor was specified as a function of the amount of waste disposed, the amount of waste recycled, and demographic characteristics. They did not consider that recycling would also be affected by the environmental quality information that a household receives from local governments and environmental agencies. Our study considers information about how violations with respect to the *maximum contaminant level* (MCL) in drinking water may affect HHW collection and recycling.

There are a few empirical studies about the generation of solid waste and recycling by households, particularly involving empirical analyses that have examined household waste behavior responses to trash price changes and regulation (van den Bergh 2008). Jenkins et al. (2003) analyzed the effectiveness of two waste programs – *curbside pick-up* and *waste drop-off* – on the rate of recycling of five different waste materials: glass bottles, plastic bottles, aluminum, newspaper, and yard waste.

In a mail survey of California households, Saphores (2006) found that gender, education, convenience, and environmental beliefs were the key factors which influenced the willingness of households to drop off electronic waste at recycling centers. There also are empirical studies on the factors which affect recycling rates that leverage county-level panel data. For example, Sidique et al. (2010) found that variable pricing of waste disposal increased the rate of recycling in counties in the state of Minnesota, and Abbott et al. (2011) found that the methods chosen for recycling collection are determinants of the observed recycling rates. In addition, the proper infrastructure of recycling facilities is critical (Bartelings and Sterner 1999).

While previous empirical studies investigated the influence of socio-economic factors, the effectiveness of waste collection programs, environmental attitudes and activism, and various waste management policies, our research evaluates the role of household informedness in the context of a special kind of waste, HHW. Household informedness is rarely discussed in the waste management literature perhaps because it is difficult to obtain data to measure the degree to which households have the necessary information to make the best decisions in managing their waste.

A few studies assessed the influence of information on recycling behavior and household recycling decisions. Martinez and Scicchitano (1998) showed that public media programs had positive effects on recycling and these effects were greater for households with higher levels of education. Nixon and Saphores (2009) found that sharing recycling information via family or friends, and at school or at work were the most effective in influencing household decisions to recycle. Largo-Wight et al. (2012) recommended educational campaigns to promote recycling behavior among college students should emphasize positive attitudes towards recycling, behavioral facilitation of recycling (e.g., convenience to recycle), the moral obligations involved, and social norms for prosocial recycling. However, these studies were mainly based on survey data and did not examine the influence of information on the amount of waste recycled. The household informedness construct in this study emphasizes how informedness influences the outcomes that are observed, especially the amount of HHW collected and recycled.

Our research represents the first empirical study to our knowledge to measure and quantify the effect of household informedness on HHW collection and recycling using county-level waste collection data. Our research contributes insights related to impact assessment of household informedness and the quantification of household informedness elasticity on HHW collection and recycling output.

An increase in HHW collection will lead to less hazardous waste being disposed of improperly so there is less polluted water and land, fewer health problems and lower expenses required for cleaning up a polluted environment. Recycled HHW also can bring extra revenue and substitute for scarce resources. By examining changes in the amount of HHW collected over time due to better household informedness, policy-makers will be able to estimate the economic and environmental benefits related to their information policies and strategies. They will be able to determine their cost-benefit relationships and the accrual timing of the impacts. In this way, they can manage information program cost planning better.

Our research questions are as follows: (1) How has household informedness influenced the amount of HHW collected? We investigate whether household informedness through public education and information on the quality of their local environment had an influence on the quantity of HHW collected. (2) Did household informedness have indirect effects on HHW that was recycled? There have not been any previous studies that measured the household's role in increasing the amount of HHW which was recycled. And yet, if greater environmental informedness results from educating households to separate their HHW properly, it may make it easier for a waste management firm to process the HHW, resulting in a higher amount of HHW recycled. (3) And how can the impact of household informedness on HHW collection and recycling output be quantified? Our approach to this question is to calculate *household informedness elasticity* of HHW collection and recycling.[3] This form of output elasticity represents the responsiveness of a change in the amount of HHW collected to a change in household informedness. This is useful for policy-makers to gauge the responsiveness of their policies and strategies that use educational campaigns and information programs to encourage a greater amount of HHW to be collected and recycled.

To answer the above research questions for recycling within California, we developed models of HHW collection with appropriate household informedness variables and socioeconomic factors. We used this model to estimate the relationships between household informedness factors and the amount of HHW collected. We then developed a more complex model that represents the relationships between the functions for the amount of HHW recycled and HHW collected (including HHW recycled and not recycled). By estimating a simultaneous equations model, we were able to gauge the direct effects of household informedness on the amount of HHW collected, and at the same time, the indirect effects of household informedness on the amount of HHW recycled. Finally, we used these estimates to calculate the

[3] The language that we are using here is akin to *price elasticity of demand* in Economics. The idea is that a unit move in price results in a change in demand due to consumers' sensitivity to having to pay more. In our case, the idea is that additional information is likely to have either a positive or a neutral effect, in that the household is able to make improved utility-maximizing decisions or freely dispose of the information if they feel that it is not needed. This is similar to price elasticity in that not everyone is sensitive to an additional dollar of price due to their income levels.

household informedness elasticity to capture the responsiveness of HHW collection and recycling output.

2.2. Theoretical Framework

Our study analyzes *household informedness* for decisions on handling waste at the household level, particularly HHW, based on utility maximization theory in consumption. We recognize two types: *informedness via public education* and *informedness via environmental information*.

Public education about HHW has long been a part of waste management in developed countries. For example, within California, information about HHW is provided in public education programs on recycling and hazardous waste, and typically uses ads, posters, brochures, newsletters, website information or special events to inform the public (CalRecycle, 2015c). These kinds of information help households to identify the potential hazards of corrosive, toxic, reactive and ignitable materials found in common household leftovers. Such programs can indirectly decrease a household's cost of HHW collection and recycling because they can improve their informedness about the best practices for handling waste, know-how about HHW, and access to various HHW collection and recycling programs. As HHW collection costs for household time and effort decrease, households collect and recycle more HHW. So we state:

- **Hypothesis 1 (Overall Effect of Public Education on HHW Collected).** *HHW-related public education increases the overall amount of HHW collected.*

HHW-related public education usually also can be used as a *source control measure* that aims to decrease the use of hazardous materials in households. It can do this through the provision of information about alternative non-hazardous materials that can replace more commonly-used, but also more hazardous products

(Lund, 2001). For example, using baking soda with white vinegar is a safer substitute for chemical oven cleaner. This kind of public information can help to reduce the generation of HHW at the source for HHW materials that have non-hazardous substitutes. Thus, we offer:

- **Hypothesis 2 (Category-Specific Direct Effect of Public Education on HHW Collected).** *HHW-related public education directly decreases the amount collected of a few HHW materials that have non-hazardous substitutes.*

HHW public education may also have an indirect effect on the amount of HHW recycled. As households become more informed about good practices in separating, storing and preparing their HHW for pick-up, it becomes easier and cheaper for a waste management organization to process the HHW for recycling. For example, leftover paints that are kept sealed in dry areas in their original containers and labels are desirable for recycling (PaintCare, 2016). They will be easier to sort and recycle than those that are not stored properly. Similarly, HHW public information often recommends that used oil should be kept in sealed, leak-proof containers and not be mixed with other liquids or debris. Following up on this advice as instructed will prevent the contamination of used oil. The contamination may make it too costly or impossible to recycle the used oil (Clean LA, 2016b). Thus, another hypothesis is appropriate:

- **Hypothesis 3 (Indirect Effect of Public Education on Overall HHW Recycled).** *HHW-related public education indirectly increases the overall amount of HHW recycled.*

Environmental quality information in the form of notifications and alerts may influence a household's perception of environmental quality and change the behavior of households. Previous studies also have shown that public notifications, information disclosures and advisories related to environmental quality have significant effects in the household's behavioral change. For example, Shimshack et al. (2007)

found that the U.S. Food and Drug Administration's (FDA) mercury advisories reduced consumption of canned fish. With the economics of household utility maximization for handling waste in mind (Morris and Holthausen, 1994), and when the cost of suffering from water contamination is more than the cost of disposing HHW properly, households prefer to participate in HHW collection programs.

We use the *number of maximum contaminant level* (MCL) *violations in drinking water* to measure the environmental quality information that households obtained, and, as a result, became aware of the quality of their environment. The number of MCL violations that occur in a county in a period depends on environmental quality there; so the higher the counts, the worse the environment quality is. This occurs due to the presence of more contaminants in the drinking water. This information is provided to the household via direct mail or via public notifications. According to the California Department of Public Health (2012), when MCL standards are violated, the water systems operator must notify the affected consumers, and these notifications are widely covered by local news media. Households whose water supplies come from large water suppliers (serving more than 10,000 people) receive annual reports about their drinking water quality by direct mail. Small water suppliers (serving fewer than 10,000 people) are only required to post such information publicly. When there are MCL violations in the drinking water, households perceive the environmental quality to be low or even unacceptable for people's health.

The households that receive this information perceive environmental quality to be low. Without this information, even though the environment quality is low, the household may not be aware of it. If households consider the perceived quality of the environment in their utility maximization when handling HHW, those that experience low environmental quality will be more motivated to dispose of their HHW properly and participate in collecting and recycling HHW. On the other hand, households living where environmental quality is perceived to be high may be less motivated to do so. Thus, we have:

- **Hypothesis 4 (Effect of Environmental Quality Information on Overall HHW Collected).** *Information on low environmental quality in a county increases the amount of HHW collected when households perceive there is a problem.*

2.3. Research Setting and Data

2.3.1. Household Hazardous Waste in California

California, the third largest and most populous state in the U.S., has 58 counties; 37 are metropolitan and 21 are non-metropolitan. They have diverse demographic characteristics, income levels, and geography. Solid waste management in the state is managed by CalRecycle (2015a), which oversees all of California's waste handling and recycling programs. Its programs include: educating the public and assisting local governments and businesses on best practices for waste management; fostering market development for recyclable materials; regulating waste management facilities, beverage container recyclers, and solid waste landfill; monitoring the recycled content of newsprint and plastic containers; and cleaning up abandoned and illegal dump sites (U.S. EPA, 2013a).

CalRecyle (2014a, 2014b) has mandated that each public agency that manages HHW in California must report the collection and disposal of the waste materials in a report called "CalRecycle Form 303." The survey data, which are published annually on CalRecycle's website, provide details on the quantity of HHW collection and disposal, based on material categories or types, collection program types, and disposal methods that are summarized below. (See Table 2.1.)

Table 2.1. Material Categories, Collection Programs and Disposal Methods, CalRecycle Form 303

MATERIAL CATEGORY	HHW COLLECTION PROGRAMS	HHW DISPOSAL METHOD
Flammable and Poison	Permanent facilities	Destructive incineration
Inorganic and Organic Acid	Mobile facilities	Fuel incineration
Inorganic and Organic Base	Temporary or periodic facilities	Landfill
Oxidizers, Peroxides, Acid, Base	Door-to-door (residential) programs	Neutralization treatment
PCB-containing	Curbside programs	Recycled
Reclaimable	Load checks	Reused
Asbestos	Others (e.g., special events)	Stabilization
Universal		Steward
Electronic		

In California, the collected HHW materials are identified in nine categories: Flammable and Poison, Acids, Bases, Oxidizers, PCB-containing, Reclaimable, Asbestos, Universal, and Electronic Waste. All these are now banned from the trash (CalRecycle, 2014a).[4] (See Figure 2.1.)

Separate laws have been passed in California and other places regarding HHW. Electronic device waste, for example, is regulated under the Electronic Waste Recycling Act of 2003. This California law requires retailers to collect Electronic Waste recycling fees from consumers upon the purchase of new or refurbished electronic products (CalRecycle, 2015b). Leftover oil-based paint (in the Flammable and Poison category) and latex paint (in the Reclaimable category) are managed by the Paint Stewardship Program (involving paint retailers) and are regulated under the California Paint Stewardship Statute of 2010 (AB 1343, Chapter 420). The California Oil Recycling Enhancement Act of 1991 requires oil manufacturers to pay

[4] *Flammable and Poison Waste* consists of flammable solids or liquids, bulk flammable liquids, oil-based paints, poisons, and reactive and explosive materials. *PCB-containing Waste* includes PCB-based paints, transformer oil, and PCB-containing ballasts (U.S. EPA, 2013b). *Reclaimable Waste* indicates automotive antifreeze and batteries, latex paint, motor oil and oil products, recyclable oil filters, and other reclaimable materials. *Universal Waste* includes things such as: mercury-switches, thermometer and novelties, mercury containing thermostats, mercury-containing waste, lamps, and rechargeable batteries. The final category is *Electronic Waste*, which includes covered, non-covered, and other electronic devices. In addition, CalRecycle (2014c) reported that conditionally-exempt small-quantity generators were allowed to dispose of some Universal Waste, such as fluorescent lamps, non-lead and non-acid batteries, mercury thermostats, and electronic devices until early 2006, but the regulations have changed.

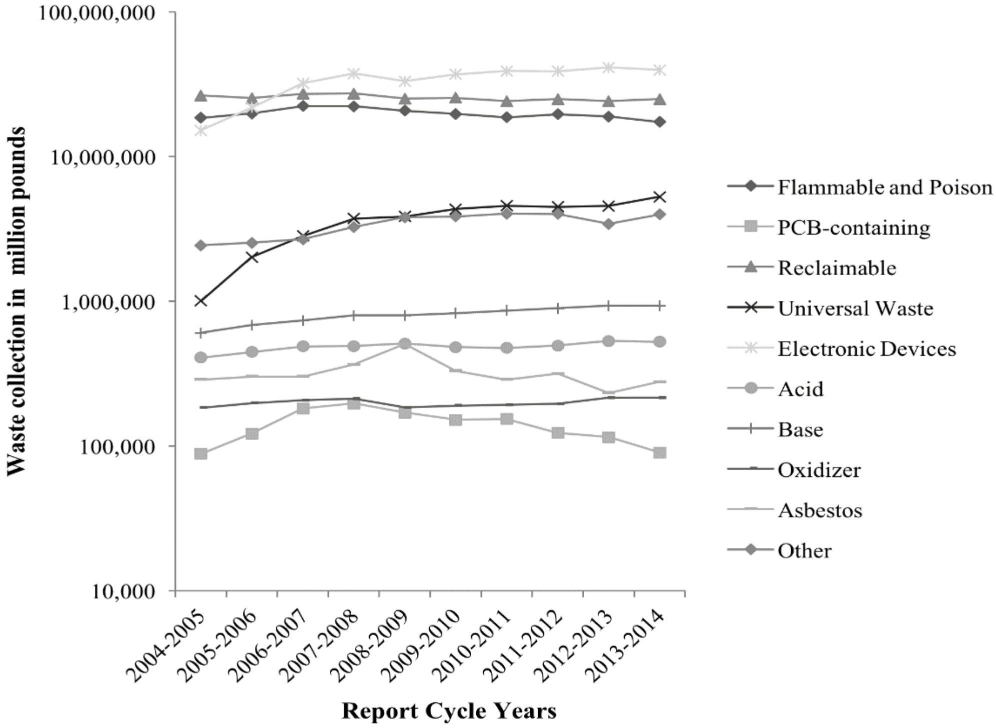
fees ($0.26 per gallon before and $0.24 after January 1, 2014) to CalRecycle for lubricating oil sold in California. Due to these specific material regulations for Electronic, Reclaimable, and Flammable and Poison Waste, it is not surprising they are the highest HHW by volume collected. (See Figure 2.1 again.)

Waste collection programs for HHW in California include permanent, mobile, temporary and periodic facilities, door-to-door residential and curbside programs, load checks, and special events, including Electronic Waste and clean-up events. More than half of total HHW have been collected by permanent facilities. Temporary facilities contributed around 20% of HHW collected since 2004, but the quantity decreased to around 10% by 2014. Recycling-only facilities have contributed only 6% of HHW. Other program types that include special HHW collection events have increased recently to about 10%.

CalRecycle (2014a) reported that more than half of total HHW have been recycled (U.S. EPA, 1997),[5] and 1-3% of HHW were landfilled in California from 2004 to 2014. By 2013, California recycled 63% of its HHW. Destructive incineration (12%) and waste stewardship (12%) are the second and third most popular disposal methods by quantity. Before 2012, the quantity of HHW disposed by fuel incineration was more than HHW disposed of by destructive incineration, but their quantity decreased gradually to 7% in 2013.

[5] HHW materials, such as used oil, precious metals, and scrap metals can be recycled and reused safely (U.S. EPA, 2000). For example, mercury can be recovered from broken thermometers. Precious metal components such as silver can be recovered from photographic fixer waste. And used oil can be refined and returned to its original purpose or processed into different oil products. Other non-recyclable materials can be processed via destructive incineration, fuel incineration, landfill, and neutralization treatment.

Figure 2.1. HHW Quantity Collected in California, by Waste Type, 2004-2014



Notes. Reclaimable Waste was the most collected HHW until Electronic Waste overtook it in 2006. In 2013, Electronic Waste accounted for 45% of total HHW (~93 million pounds), followed by the Reclaimable Waste (25%) and then the Flammable and Poison Waste categories (19%). Aerosol Container Waste collection was separately reported in the CalRecycle Form 303 until the 2005-2006 report cycle. Since 2006, non-empty aerosol containers are included in Universal Waste, and Flammable and Poison Waste, and other HHW, based on the contents of the containers (CalRecycle, 2014a).

2.3.2. Data and Variable Description and Construction

For this discussion, the reader should refer to Table 2.2 with the definitions of the study variables.

Census data at the county level. County-level census data are used to represent characteristics of the counties and demographic characteristics of households living in California. We collected data from public sources, such as the American Community Survey (U.S. Census Bureau, 2012). The data from 2005 to 2012 include county mean household income, population, density per capita, and education level (via the percentage of high school graduates).[6] Reporting agency-level census data were not available; so we assumed that each agency had similar characteristics as others in the same county, thereby allowing us to match the reporting agencies with the respective county characteristics.

Table 2.2. Variable Definitions

VARIABLE NAMES	DEFINITIONS
HHW collection	
HHWCollQ	Quantity of HHW collection (in pounds)
ReclCollQ	…………………………… – Reclaimable Waste (in pounds)
FPCollQ	…………………………… – Flammable and poison Waste (in pounds)
EWCollQ	…………………………… – Electronic Waste (in pounds)
AcidCollQ	…………………………… – Acid Waste (in pounds)
AsbCollQ	…………………………… – Asbestos Waste (in pounds)
BaseCollQ	…………………………… – Base Waste (in pounds)
OxCollQ	…………………………… – Oxidizer Waste (in pounds)
PCBCollQ	…………………………… – PCB-containing Waste (in pounds)
UWCollQ	…………………………… – Universal Waste (in pounds)
County characteristics	
Pop	County population from 2004 to 2012 (in millions of people)
MeanHHInc	County mean household income from 2004 to 2012 ($000s)
LandArea	County land area (in 000s of square feet)
Density	County density (in 000s of square feet per capita)
EduHS%	Percent population over 25 years old who earned a high school diploma
Household informedness	
3YCum#PubEdu	3-year cumulative number of projects with public education program that received HHW grant(s)
#MCLViolLg	Number of MCL violations for large water suppliers of drinking water
#MCLViol	Total number of MCL violations
Other factors	
RUCC	Rural-urban continuum code, 1 to 5, with 1 as the base case
DHHWGrant	Binary variable to indicate whether HHW grant(s) awarded
HHWRecQ	Quantity of recycled HHW in pounds
EWasteFee	Electronic Waste recycling fee based on the Electronic Waste Recycling Act of 2003
UsedOilFee	Used oil fee required to be paid by oil manufacturers based on Senate Bill 546; this represents the fee change in California Oil Recycling Enhancement Act
#CCNews	Number of news articles from county-level news sources on climate change
#CCNewsCA	Number of news articles from California state-level news sources
#CCNewsIdw	Number of news articles from county-level news sources with inverse weighted distances for counties (that had no news articles themselves) from others that had them for county seat geo-coordinates

Proxies for household informedness. To investigate the effect of household

[6] County data for 2004 were *backwards extrapolated* by using the annual growth rate in historical data from 2005 to 2012.

informedness, we use data that proxy for public education and environmental quality information. For the HHW public education variable, we extracted the data from the CalRecycle HHW grant database (www.calrecycle.ca.gov/homehazwaste/Grants). This database contains the amount of grant awarded to waste facilities or agencies for HHW-related projects. We searched project descriptions for the words "public education" or "public information," and marked projects that include HHW public education. Then, we counted the projects for each county in each year. These were used to create a variable for the three-year cumulative number of projects with HHW public education to proxy for HHW-related public education. We use the three-year cumulative number of projects, based on the idea that HHW public education may have a cumulative effect in the following years; this is similar to Sidique et al.'s (2010) approach.

To represent environmental quality information, we acquired the number of *maximum contaminant level* (MCL) and water quality monitoring violations records from the annual compliance report by California Department of Public Health, submitted to the U.S. Environmental Protection Agency from 2004 to 2012. This data includes type of violation, violation counts, and number of population affected.

County type stratifiers. We used *county classification* based on the 2013 *Rural-Urban Continuum Codes* (*RUCC*) published by the U.S. Department of Agriculture's Economic Research Service (2013). It distinguishes among metropolitan counties by their population size and non-metropolitan counties by their *degree of urbanization* and *adjacency to a metro area*. (See Appendix A, Tables A1-A2 for details.)

Regulation-related proxies. During our study period, there were two regulations that may have affected the collection of HHW. First, California's Electronic

Waste Recycling Act of 2003 regulated recycling fees for covered Electronic Waste based on the size of the video display devices. These categories were: (1) more than 4 but less than 15 inches; (2) at least 15 but less than 35 inches; and (3) 35 or more inches (CalRecycle, 2016a). Since we use aggregate HHW data for our data analysis, we employ the average value of the fee of all categories: $8 in 2005 to 2008; $16 in 2009 to 2010; and $8 again in 2011 to 2012.

We captured this change in the variable *EWasteFee* in our models to control for the influence of the Electronic Waste Recycling Act. Second, Senate Bill 546 (Lowenthal, 2009), signed in 2009, made changes to the earlier California Oil Recycling Enhancement Act. The changes took effect in 2010. They were: the restructuring of lubricating oil recycling fees; a used oil recycling incentive payment system; streamlining of the used oil grant program; and better handling and management of used oil. According to this bill, the fee was $0.16/gallon in 2004-2009 and $0.26/gallon in 2010-2013. This change is represented in the variable *UsedOilFee* to control for the influence of California Oil Recycling Enhancement Act on the amount of HHW collected.

County and state-level news about climate change. We captured *state-level* and *county-level news articles* related to climate change from Factiva (1999). Climate change is a well-known topic that may affect local environmental policies. News of climate change may have encouraged more environmental sustainability projects like HHW public education, but it does not have any direct effects on HHW collection. Thus, it can be used as an instrumental variable for HHW public education to address endogeneity. The state-level news articles on climate change came from California sources, such as the *Inside Cal / EPA* newsletter, *The Recorder* (California edition), and *California Builder and Engineer* magazine. The county-level news data only covered 15 counties in California, so we estimated the news effects in counties that had no local news sources for climate change based on their proximity to those that had such sources. We assume that news spilled over from one county to neighboring counties; the nearer ones would have a higher effect than more distant ones. So we applied an *inverse distance weighting function* to impute the effects of news in neighboring counties.[7]

Creation of the panel dataset with the study variables. The descriptive statistics in Table 2.3. To produce this panel dataset, we combined the aggregate HHW collection, disposition, county characteristics, household informedness and other variables, based on the county and report cycle year.

The American Community Survey did not provide demographic characteristics data for a few counties in some years. We also could not obtain HHW data from a few counties in some years, for example, Lake County only reported the HHW collected amount in 2007-2008; and Madera County did not report the HHW collected amount 2004-2005 or 2006-2007. So we had to omit rows with missing values. We also ran a Bonferroni outlier test (Fox and Weisberg, 2011) to detect any extreme or unusual data points, which led to the removal of one county-level data point from our panel data. As a result, the panel data contain 333 data points for 39 counties.

[7] The calculation is: $\#CCNewsIdw_c = \frac{\sum_{c'} w_{c'} \#CCNews_{c'}}{\sum_{c'} w_{c'}}, if\ dist(c, c') \neq 0$, and $\#CCNewsIdw_c = \#CCNews_c,\ if\ dist(c, c') = 0$, where $w_{c'} = \frac{1}{dist(c,c')^2}$. *#CCNewsIdw* is the imputed number of climate change-related news articles; *#CCNews* is the number of climate change related news articles; *c* is the index for a county, *c′* is the index for a county other than county *c*. *d*(*c,c'*) is a distance function calculated between a coordinate in county *c* and in county *c′* using the *Haversine method*, which assumes a spherical earth. We use the longitude and latitude of the *county seat* as the point coordinate in the county because the county seat usually is the most populous city in the county. So we use it as the *population center* of a county. Previous studies, such as McConnell (1965), used the coordinates of county seats as the population centers, instead of the *mathematical centroid*.

Table 2.3. Descriptive Statistics for the Variables

VARIABLES	MEAN	STDDEV	MEDIAN	MIN	MAX	SKEW	KURTOSIS
Pop	969,056	1,665,021	415,825	63,986	9,946,947	4.14	18.80
Density	961	2,653	185	25	17,546	5.39	29.64
EduHS%	0.82	0.08	0.84	0.62	0.96	-0.59	-0.56
MeanHHInc	75,247	18.567	73,343	47,002	137,575	0.78	0.15
DHHWGrant	0.37	0.48	0	0	1	0.53	-1.73
3YCum#PubEdu	0.49	0.79	0	0	4	1.60	2.01
#MCLViol	11	35	0	0	254	4.54	22.42
#MCLViolLg	0.72	2.46	0	0	4	1.60	2.01
HHWCollQ	2,262,873	3,056,300	1,417,106	49,305	23,867,787	3.97	18.79
ReclCollQ	660,211	711,997	397,820	0	3,998,194	2.15	5.54
FPCollQ	530,349	806,967	290,539	0	5,822,124	3.57	14.93
EWCollQ	837,943	1,494,284	480,143	0	15,267,130	5.34	38.04
AcidCollQ	12,745	18,415	6,736	0	113,578	3.15	11.24
AsbCollQ	7,783	18,084	200	0	183,440	4.47	30.39
BaseCollQ	21,118	38,217	8,283	0	244,957	3.68	14.82
OxCollQ	5,182	6,983	2,412	0	41,824	2.62	7.98
PCBCollQ	3,693	5,694	1,866	0	41,107	3.80	17.47
UWCollQ	90,997	108,818	61,215	0	625,152	2.38	6.37
ln(*HHWCollQ*)	14.11	1.04	14.16	10.81	16.99	-0.19	0.49
ln(*HHWRecQ*)	13.62	1.28	13.77	2.30	16.76	-2.33	17.46
#CCNewsCA	156	110	167	0	325	-0.10	-1.16
#CCNewsIdw	9	19	3	0	137	4.00	18.26
EWasteFee	8.94	4.57	8	0	16	0.01	-0.08
UsedOilFee	0.19	0.05	0.16	0.16	0.26	0.68	-1.55

2.4. Empirical Models

We next present our empirical research strategy and methods to analyze the influence of household informedness based on the county-level data that we gathered.

2.4.1. Empirical Research Strategy and Methods

We estimate a model of HHW collection that is a function of appropriate household informedness variables and socioeconomic factors. We begin with a linear and separable fixed-effects model to estimate the association between household informedness and HHW collection. Then we use a *two-stage least squares* (2SLS) model to acquire causal estimates of informedness-driven HHW collection.

Estimating the indirect effects of household informedness on the amount of HHW recycled requires an understanding of the relationship between the linear functions for the total HHW collected and recycled. This is because these outcome variables are likely to be jointly determined, and HHW recycling may influence the amount of HHW that is not recycled. For this kind of situation, the use of a simultaneous equations model is suitable (Greene, 2012; Wooldridge, 2002).

We develop a system of equations to represent the demand functions and estimate the effects of informedness on the amount of HHW that is collected and HHW that is recycled. The resulting system of equations model is estimated using *seemingly unrelated regression* (SUR), which recognizes the cross-correlation of the equations' error terms (Zellner, 1962). This allows us to estimate these together instead of separately. Thereafter, we shift to estimate a two-stage least squares (2SLS) model with instrumental variables. Finally, we use a *three-stage least squares* (3SLS) model that combines SUR and instrumental variables estimation together with 2SLS. Household informedness elasticity of HHW collection and recycling output is calculated using the 3SLS estimation results.

In the extended analysis, we stratify the fixed-effects model by material category and estimate the coefficients of the model by using 2SLS for each material category. Some counties did not report waste collection for some HHW material categories in certain years, however. The decision to collect certain HHW materials by local governments may have depended on factors such as household income, education level, and grant awards provided. So we suspect there was some selection bias in the material-specific models. To correct this bias, we re-estimate the models using Heckman's two-step method.

The modeling and estimation process is summarized in Appendix B. We next discuss the baseline model for HHW collection. We distinguish between HHW that is collected and then recycled.

2.4.2. Model 1: HHW Collection

We start with a baseline model in which HHW collection is a function of household informedness via public education and environmental quality information. This model allows us to estimate the impact of informedness on HHW collection outputs. If we stratify this model by HHW material category, we can also observe different influences of informedness on certain HHW materials. The model is:

$$\ln(HHWCollQ_{ct}) = \gamma_0 + \gamma_1 3YCum\#PubEdu_{ct} + \gamma_2 \#MCLViolLg_{ct} + \gamma_3 \#MCLViol_{ct} + \gamma_4 DHHWGrant_{ct} + \gamma_5 \ln(Density_{ct}) + \gamma_6 EduHS\%_{ct} + \gamma_7 \ln(MeanHHincome_{ct}) + \gamma_8 \ln(Pop_{ct}) + \gamma_9 EWasteFee_{ct} + \gamma_{10} UsedOilFee_{ct} + \sum_{r=2}^{5} \theta_r \, RUCC_r + \varepsilon_{ct}, \quad (1)$$

with subscripts for county *c* and report cycle year *t*.

Household informedness via public education is proxied by the three-year cumulative number of projects with a public education program (*3YCum#PubEdu*). Environmental quality information is proxied by two things. One is the total number of MCL violations (*#MCLViol*) in the county regardless of the size of the water suppliers. This variable is a proxy for the environmental quality that households perceive when they were informed about these MCL violations via direct mail, public notices, newspapers or other media. A large number of MCL violations represents lower environmental quality, and a lower number represents higher environmental quality. The other is the number of MCL violations from large water suppliers that are sent to households via direct mail (*#MCLViolLg*). This proxy variable represents information about the number of MCL violations delivered directly to households. We include it because MCL violation information may affect HHW collection when it is sent directly to households.

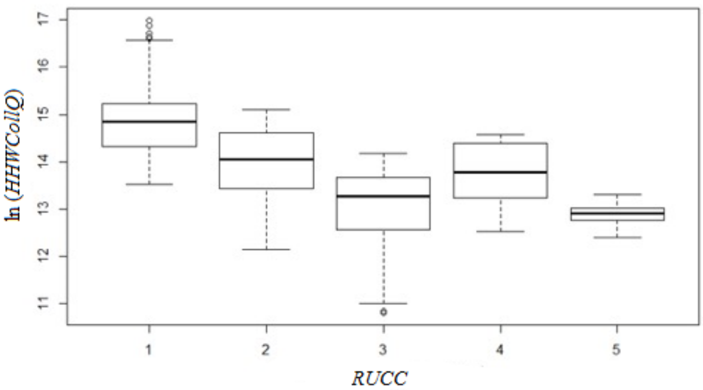
Based on previous studies, we expect that the variation in waste collection and recycling activities generally is influenced by socioeconomic factors: household income, population, density, and education level (Richardson and Havlicek, 1978). These factors cannot be controlled easily by waste management policy-makers, but are useful to predict and explain waste collection patterns, and the recycling behavior of people living in different counties. People's behavior with respect to HHW ought not to be the same as for general trash, so we use these factors as control variables to account for county variability in HHW collection.

Regarding the socioeconomic factors, we expect more educated people to be more aware of the risks of HHW and that they can easily obtain information related to HHW and environmental quality. Households with higher incomes have more time and opportunities to participate in HHW collection programs or deliver their waste to HHW facilities. Counties with more population generate more waste, and this is the same case as for general trash. On the other hand, population density may be negatively associated with the quantity of HHW collected because high population density in the county may discourage people from participating in HHW collection programs due to socioeconomic reasons that are unobservable.

We use a binary variable to indicate whether a county received grants for HHW projects (*DHHWGrant*) as a control. In California, HHW grants are awarded to help local waste management agencies to establish or expand HHW collection programs by conducting various projects such as to upgrade the existing HHW collection facilities, to hold free HHW collection events, to purchase new processing machines, to educate the public regarding improper disposal of HHW, and so on. These projects provide more opportunities for households to participate in HHW collection programs so the counties that receive the grants may produce a higher amount of HHW collected than the ones that do not receive them. Higher priority was given to new HHW programs in rural areas, under-served areas, and multi-jurisdictional HHW programs. Greater emphasis was also given to applicants (cities, counties, qualifying Indian tribes, and local agencies) that had not received HHW grants in the two previous cycle years.

The *RUCC*s distinguish the counties based on their *degree of urbanization* and *adjacency to a metro area*. (See Figure 2.2.) We observe that this classification seems to matter. The average of the HHW collection amount is the highest for the base case for $RUCC_1$, followed by $RUCC_2$, $RUCC_4$, $RUCC_3$, and $RUCC_5$. Thus, we also include this categorical variable as one of the controls in our model.

Figure 2.2. Boxplot of HHW Collection Amount by Rural-Urban Continuum Codes (for fixed-effects)



$RUCC_1$:	Counties in metro areas of 1 million population or more.
$RUCC_2$:	Counties in metro areas of 250,000 to 1 million population.
$RUCC_3$:	Counties in metro areas of fewer than 250,000 population.
$RUCC_4$:	Urban population of 20,000+ and adjacent to metro area.
$RUCC_5$:	Urban population of 20,000+ and not adjacent to metro area.
ln (*HHWCollQ*):	Natural log of HHW collection amount in pounds.

2.4.3. Model 2: HHW Collected Versus HHW Collected and Recycled

We next specify a model that recognizes the simultaneity of HHW that is collected versus HHW that is collected and recycled. The simultaneity captures a more realistic representation of the underlying process in HHW collection and recycling.

Not all HHW collected is recycled; some is recycled and some is not recycled. Using this model, we want to know if there are indirect effects of household informedness on the amount of HHW recycled. The system, for county *c* and report cycle year *t*, is:

$$\ln(HHWCollQ_{ct}) = \alpha_0 + \alpha_1 \ln(HHWRecQ_{ct}) + \alpha_2\, 3YCum\#PubEdu_{ct} + \alpha_3\, \#MCLViolLg_{ct} + \alpha_4 \#MCLViol_{ct} + \alpha_5 DHHWGrant_{ct} + \alpha_6 \ln(Density_{ct}) + \alpha_7\, EduHS\%_{ct} + \alpha_8 \ln(MeanHHIncome_{ct}) + \alpha_9 \ln(Pop_{ct}) + \varepsilon_{ct} \quad (2)$$

$$\ln(HHWRecQ_{ct}) = \beta_0 + \beta_1\, 3YCum\#PubEdu_{ct} + \beta_2\, \#MCLViolLg_{ct} + \beta_3 \#MCLViol_{ct} + \beta_4\, DHHWGrant_{ct} + \beta_5 \ln(Density_{ct}) + \beta_6\, EduHS\%_{ct} + \beta_7 \ln(MeanHHIncome_{ct}) + \beta_8 \ln(Pop_{ct}) + \beta_9 EWasteFee_{ct} + \beta_{10} UsedOilFee_{ct} + \sum_{r=2}^{5} \theta_r\, RUCC_r + \epsilon_{ct} \quad (3)$$

If HHW public education can successfully inform households about how to store and sort their HHW properly, the amount of HHW collected and recycled (*HHWRecQ*) may increase. Thus, we expect to find a positive effect of HHW public education (*3YCum#PubEdu*) on HHW recycled. On the other hand, HHW public education may have positive effects on the amount of HHW collected, however, a change in the amount of HHW collection associated with HHW public education may also arise from source reduction. To capture the unobserved source reduction, we include *HHWRecQ* on the right-hand side of *HHWCollQ* equation as a control variable. Doing so allows us to measure the effects of HHW public education (*3YCum#PubEdu*) on the amount of HHW collected (*HHWCollQ)* while holding the amount of HHW recycled constant (*HHWRecQ*). This also enables us to observe the association between the amount of HHW collected (*HHWCollQ*) and the amount of HHW collected and recycled (*HHWRecQ*). The specification of the relationship between the functions is similar to that of Callan and Thomas (2006).

Similarly, we believe that information on low environmental quality likely encourages HHW recycling, particularly when it is provided directly to households. So we expect to find positive effects of *#MCLViolLg* and *#MCLViol* in the *HHWReqQ* equation. We also included these variables in the *HHWCollQ* equation because a change in the HHW collected due to environmental quality information may arise from source reduction as HHW public education yields more household informedness.

We use a binary variable for the availability of HHW grant awards and socio-economic factors (household income, population, density, and education level) as control variables in both equations. These are the same controls as in the HHW Collection Model (Model 1).

Similar to the study by Callan and Thomas (2006), the inclusion of *HHWRecQ* in the *HHWCollQ* Equation 2 allows us to decompose the effects of the household informedness variables into direct and indirect effects through *HHWRecQ*. Based on the model specification, we can calculate the household informedness elasticity of HHW collection output, *Elasticity*, for public education as follows:

$$
\begin{aligned}
Elasticity &= \left(\frac{d\ln(HHWCollQ)}{d3YCum\#PubEdu}\right)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\
&= \left(\frac{\partial\ln(HHWCollQ)}{\partial 3YCum\#PubEdu}\right)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\
&\quad + \left[\left(\frac{\partial\ln(HHWCollQ)}{\partial\ln(HHWRecQ)}\right)\left(\frac{\partial\ln(HHWRecQ)}{\partial 3YCum\#PubEdu}\right)\right]\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\
&= \alpha_2\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) + \alpha_1\beta_1\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \\
&= (\alpha_2 + \alpha_1\beta_1)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right) \qquad (4)
\end{aligned}
$$

The first term in Equation 4, $\alpha_2 \left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right)$, is the effect of HHW public education, as it is made available, on HHW collection, with the amount of recycled HHW held constant. It captures source reduction activity due to public information on non-hazardous household products that can replace hazardous household products. The second term is derived from the equation for HHW collection. It estimates the indirect effects of HHW public education on HHW recycled. This includes the change in the amount of HHW collected from changes in the amount of recycled due to the influence of public education. We also calculated the household informedness elasticity of HHW collection via environmental quality information, as in Equation 4.

2.5. Estimation Results

We next present our modeling process and estimation results for the HHW Collection Model (Model 1) with fixed-effects and 2SLS. Then we offer a discussion of the estimation results for the HHW Collected Versus HHW Collected and Recycled Model (Model 2) with 3SLS.

2.5.1. Model 1: Baseline and 2SLS Estimation Results

Table 2.4 presents the results using a baseline fixed-effects model and a 2SLS fixed-effects model. The coefficient estimate of HHW public education was not significant in the fixed-effects baseline model. (See Table 2.4, Fixed-Effects Baseline Model.) This estimation did not address the endogeneity of the HHW public education variable. For MCL violation information though, we found that when information was sent directly via mail, an increase of one MCL violation was associated with a small but still significant increase in the amount of HHW collected of 4% (= $e^{0.04}$ – 1, calculated from the coefficient 0.04, $p < 0.05$). But, in general, an increase of one MCL violation was associated with a decrease by 0.5%

(= $e^{-0.005} - 1$, from the estimated coefficient -0.005, $p < 0.01$) of the HHW amount collected.

Table 2.4. Fixed-Effects Model Estimation Results

	FIXED-EFFECTS BASELINE MODEL	**FIXED-EFFECTS ESTIMATED WITH 2SLS**
VARIABLES	**COEF. (SE)**	**COEF. (SE)**
Intercept	-8.23*** (2.82)	-8.28*** (2.84)
3YCum#PubEdu	0.07 (0.05)	-0.04 (0.15)
#MCLViolLg	0.04*** (0.02)	0.04*** (0.02)
#MCLViol	-0.005*** (0.001)	-0.005*** (0.001)
DHHWGrant	0.10 (0.08)	0.15 (0.10)
ln(*Density*)	-0.09** (0.04)	-0.09** (0.04)
EduHS%	3.33*** (0.61)	3.22*** (0.64)
ln(*MeanHHIncome*)	1.06*** (0.25)	1.04*** (0.25)
ln(*Pop*)	0.62*** (0.06)	0.64*** (0.07)
EwasteFee	0.01 (0.01)	0.02 (0.01)
UsedOilFee	0.49 (0.84)	0.28 (0.90)
$RUCC_2$	-0.02 (0.11)	-0.03 (0.11)
$RUCC_3$	-0.11 (0.16)	-0.07 (0.17)
$RUCC_4$	0.42** (0.21)	0.44** (0.21)
$RUCC_5$	-0.60** (0.26)	-0.53* (0.28)
Adj. R^2	66.6%	66.2%

Notes. Baseline model: fixed-effects; dep. var.: ln (*HHWCollQ*); 333 obs. Base case $RUCC_1$ is omitted. For 2SLS, instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*, weak instruments stat. = 37.27***; Wu-Hausman = 0.53. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We next performed a 2SLS estimation with the number of news articles related to climate change from California state-level news sources (*#CCNewsCA*) as an instrumental variable for the endogenous HHW public education variable. The *weak instruments statistic* results showed that our instrumental variable was not weak, while the Wu-Hausman test statistic implied that the fixed-effect estimates and the estimates with 2SLS were both consistent so the endogeneity might not matter. [8] We did not use *#CCNewsIdw* as an instrumental variable because the weak instrument statistic was not significant; thus it would be a weak instrument in the model, and so not useful. The 2SLS coefficient estimate of household informedness via public education was -0.04 ($p = 0.81$, not significant). We suspect that HHW public education's effects on HHW generation were not captured very well in this model.

[8] This statistic is from an F-test of the first-stage regression for weak instruments (Kleiber and Zeileis 2015).

For MCL violation information, the estimates were the same as those of the baseline model estimates.

In both estimations, the county characteristics had the same signs as expected. The estimates of *EduHS%*, *MeanHHIncome*, and *Pop* were positive and significant. So the higher the percentage of high school graduates, mean household income, and county population, the larger was the quantity of HHW collected. The coefficient of higher population *Density* in a county was negative; this shows that the higher the population density, the lower was the amount of HHW collected.

The counties in $RUCC_4$ had an average about 55% (= $e^{-0.44} - 1$, from the estimated fixed effect 2SLS coefficient of 0.44, $p < 0.05$) more than the amount of HHW collected in the counties in $RUCC_1$ while holding the other variables constant. This is surprising because $RUCC_4$ counties are non-metropolitan with an urban population of 20,000 or more and are adjacent to a metropolitan area. These include Lake, Mendocino, and Nevada Counties in our panel data. Although the average amount of HHW collection in these counties was only about 1.1 million pounds per year, the HHW collection density ranged from 3.1 to 21.8 pounds/person in a year. This suggests that some counties in this area may have been actively collecting HHW, or these counties may have been collecting HHW from the residents of the neighboring counties as well. Further geospatial analysis needs to be performed to investigate this peculiarity.

2.5.2. Model 2: System of Equations Estimation Results

To adjust our analysis to achieve a more realistic representation of the underlying process, we developed a system of equations that included dependent variables for HHW collected and HHW recycled. Our estimation strategy was to start with seemingly unrelated regression for the multi-equation system, recognizing the commonality in the information in the error terms.[9] But this left out any consideration of the endogeneity of variables and true simultaneity in the processes. So we switched to a more realistic representation of the system involving simultaneous equations – 3SLS estimation that enables us to address the endogeneity of the household informedness variables. The instrumental variable, *#CCNewsCA*, was used again to correct for the possible endogeneity bias in the HHW public education variable.

The SUR and 2SLS estimation results are shown in Appendix C, Tables C1 and C2. The Hausman test for 3SLS consistency was 36.76 and greater than 0.05 (p = 0.06). So we concluded that the 3SLS estimates were consistent and more efficient than the 2SLS estimates. (See Table 2.5 for the 3SLS results.)

The coefficient estimates for county characteristics variable have the same signs in the *HHWCollQ* and *HHWRecQ* equations. These were also the same as the corresponding estimates in the fixed effect model (Model 1). The coefficient estimate for the HHW recycled variable was significant and positive at 0.50. This means that a 1% increase in the amount of HHW collected was associated with a small 0.5% increase in the amount of HHW recycled. Our interpretation is that the amount of HHW recycled increased proportionately more than the amount of HHW collected (recycled and not recycled).

The estimate for the *3YCum#PubEdu* variable in Table 2.5 for *HHWRecQ* is 0.48 ($p < 0.10$) and it had somewhat less of its variation explained – only 39.5%. The results still suggest that the provision of one project with HHW public education in a county was associated with an indirect increase in the amount of HHW

[9] SUR estimation only allows us to model the cross-equation error term correlations.

recycled by about 61.5% (= $e^{0.48}$ - 1). On the other hand, the coefficient estimate for this variable in the *HHWCollQ* equation is -0.14 and it is significant too ($p < 0.10$). Plugging these coefficients into Equation 4, the informedness elasticity of HHW collection output for public education $(\alpha_2 + \alpha_1\beta_1)\left(\frac{3YCum\#PubEdu}{\ln(HHWCollQ)}\right)$, evaluated at the point of means was 0.003 (= (-0.14 + 0.50 × 0.48) ×0.49/14.11).

Table 2.5. 3SLS Estimation Results for HHW Collected Versus HHW Collected and Recycled

VARIABLES	HHW COLLECTED	HHW COLLECTED AND RECYCLED
	COEF. (SE)	COEF. (SE)
Intercept	-3.70** (1.70)	-10.59** (4.72)
ln(*HHWRecQ*)	0.50*** (0.03)	—
3YCum#PubEdu	-0.14* (0.08)	0.48* (0.25)
#MCLViolLg	0.02* (0.01)	0.04 (0.03)
#MCLViolL	-0.003*** (0.001)	-0.004* (0.002)
DHHWGrant	0.16** (0.06)	-0.18 (0.17)
ln(*Density*)	-0.05 (0.03)	-0.11 (0.07)
EduHS%	1.54*** (0.39)	4.13*** (1.06)
ln(*MeanHHIncome*)	0.50*** (0.17)	1.22*** (0.42)
ln(*Pop*)	0.34*** (0.04)	0.57*** (0.11)
EWasteFee	—	0.00 (0.02)
UsedOilFee	—	1.51 (1.48)
$RUCC_2$	—	0.06 (0.18)
$RUCC_3$	—	-0.04 (0.28)
$RUCC_4$	—	0.59* (0.36)
$RUCC_5$	—	-1.20** (0.47)
Adj. R^2	81.7%	39.5%

Notes. Model: simultaneous eqns.; estimation: 3SLS; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Estimated with SystemFit package in R (Henningsen and Hamann 2007). Signif.: *** < 0.01, ** < 0.05, * < 0.10.

We also found that when information about an increase in the MCL violations was released at the county level, it was associated with a decrease in the amount of HHW recycled of about 0.4%. This suggested that the county could have been doing more in advance of the MCL violation information dissemination to improve HHW recycling, if only on the margin. From this, we estimate the household informedness elasticity of HHW collection output for MCL violations was -0.004 (= (-0.003 + 0.50 × -0.004) ×11/14.11), again quite small. A more interesting finding is that when such MCL violation information was sent directly to households via postal mail, this was associated with an increase of around 2% for HHW collection. We also estimate that informedness elasticity of HHW collection for environmental information related to MCL violations information via direct mail was about 0.001 (= (0.02 + 0.50 × 0) ×0.72/14.11). Note that this variable is not significant for *HHWRecQ* so this information may or may not increase the amount of HHW recycled. Table 2.6 summarizes the household informedness elasticities of HHW collection and recycling. The magnitudes of these estimated values were less than 1, so we conclude that HHW collection and recycling in California were relatively *informedness-inelastic*. (See Table 2.6.)

Table 2.6. Household Informedness Elasticities of HHW Collection and Recycling Outputs

HOUSEHOLD INFORMEDNESS ELASTICITY OF:	ESTIMATED ELASTICITY VALUE
HHW Collection Output	
HHW public education	0.003 ($p < 0.10$)
MCL violations information	-0.004 ($p < 0.10$)
MCL violations information via direct mail	0.001 ($p < 0.10$)
HHW Recycling Output	
HHW public education	0.017 ($p < 0.10$)
MCL violations information	-0.003 ($p < 0.10$)
MCL violations information via direct mail	0.000 ($p > 0.10$)

Notes. The estimated values of household informedness elasticity of HHW collection and recycling outputs suggest their responsiveness to changes in informedness. These values are significant, but only at the 10% level, except for MCL violation information via direct mail for HHW recycling output, which is not different from zero ($p > 0.10$). The estimated informedness elasticity for HHW collection outputs was calculated as in Equation 4, evaluated at the point of means. This includes the direct effect of household informedness on HHW collection outputs, and the indirect effect of household informedness on HHW recycling output. The estimated elasticity value for HHW recycling output was derived from the coefficient estimates of the household informedness variables in Equation 3, also evaluated at the point of means. The significance level of informedness elasticity is the smallest level of significance of the coefficient estimates used to calculate it. The idea is that the aggregate significance level of the estimated predication is no greater than that of the least significant component that has an effect on the aggregate value.

The estimation that we made for household informedness elasticity of HHW collection output for HHW public education deserves further discussion. The coefficient estimates of *3YCum#PubEdu* in the *HHWCollQ* and *HHWReqQ* equations were significant ($p < 0.10$), but with different signs. The negative estimate of *3YCum#PubEdu* in the *HHWCollQ* equation gives evidence of a possible negative effect of HHW public education on the amount of HHW collected. Additionally, the coefficient estimate of 0.04 for *#MCLViolLg* in the *HHWRecQ* equation had a standard error of 0.03 (p = 0.12, not significant). This result suggests that MCL violation information sent via mail mattered in terms of HHW collection, but it may not have had any effect on HHW recycling. Beyond this, the other coefficient estimates in the elasticity computation were significant, suggesting public education and MCL violation information mattered for collection and recycling. We include significance estimates for the informedness elasticities below.

2.6. Extended Model for the Categories of Household Hazardous Waste

In this section, we discuss some extended models to estimate the amount of HHW collected by HHW material category. The estimation results of these models show that the provision of HHW public education had negative effects on HHW collection outputs in some circumstances. They are related to a couple HHW material categories that represent household products which have alternatives that household consumers can buy that use non-hazardous materials. We present the estimation results for the HHW collection output stratified by material category.

HHW-related campaigns and outreach may have motivated and encouraged households to recycle their HHW and participate in HHW collection programs. However, they may also have caused waste source reduction. Model 1 did not capture the changes in the provision of HHW-related public education that led to waste source reduction. Since waste source reduction was most likely to happen for HHW materials that had non-hazardous and more efficient substitutes, we extended the analysis using Model 1 by stratifying the prior estimation model via the material categories. When the effect of HHW-related public education that led to source reduction was stronger in motivating households to recycle, we expected to see a negative coefficient for the HHW-related public education variable in the model.

We also estimated the HHW collection models for each of the HHW material categories. The dependent variable in the model is the natural log of the HHW amount collected for each material category: Reclaimable Waste (*ReclCollQ*), Flammable and Poison Waste (*FPCollQ*), Electronic Waste (*EWCollQ*), Acid Waste (*AcidCollQ*), Asbestos Waste (*AsbCollQ*), Base Waste (*BaseCollQ*), Oxidizer Waste (*OxCollQ*), PCB-containing Waste (*PCBCollQ*), and Universal Waste (*UWCollQ*). The purpose was to analyze the informedness effects and other factors on HHW collection outputs that may have varied among different material categories. The material categories' 2SLS estimation results are provided in Appendix D, Table D1, with PCB-containing and Universal Waste omitted due to poor model fit.

We observe that some counties did not collect waste in certain HHW material categories in certain years. Some selective HHW collection programs were not available in small counties. For example, Madera County did not report any material collection before 2005. Also, Lake County only collected Electronic and Universal Waste in 2007-2008. And San Luis Obispo, Kern, Madera and Imperial County did not collect Asbestos Waste during our study period. In some other counties, there were zero values for a few HHW materials in some years. For example, Humboldt County reported that it collected Electronic Waste only in Report Cycle 2006-2007 to 2008-2009, while Mendocino County collected Electronic Waste in Report Cycle 2004-2005 to 2006-2007. These led us to consider the possibility of selection bias in HHW material-specific collection output amounts.

So we estimated the coefficients of the baseline model stratified by the material category using *Heckman's two-step estimation method*. This let us resolve possible sample selection bias, as in Suwa and Usui (2007). In the first step, we employed a probit estimation model and identified the factors that may affect a local government's decision on whether to collect waste in a specific HHW material category. These factors include the percentage of high school graduates, mean household income, and the number of HHW grants in a county. The probit analysis results are provided in Appendix D, Table D3. The probit analysis showed a positive and significant coefficient for mean household income related to Acid, Base, Oxidizer, and Asbestos Waste. This means that household income influenced the decisions of local waste managers as to whether they collected the HHW material; counties with higher household income had a higher probability to collect these HHW materials. The HHW grant variable (*DHHWGrant*) estimate was positive and significant only for Base and Asbestos Waste.

Based on this estimation, we derived the *inverse Mills ratio* and added it to Model 1 that explains the variance in the quantity of HHW material collected. We also used the instrumental variable *#CCNewsCA* in place of the endogenous HHW public education variable. The results for the fixed-effects model with Heckman's method are provided in Appendix D, Table D2. There was evidence of selection bias only for Oxidizer Waste, for which the inverse Mills ratio was significant (p = 0.01).

The coefficient estimate of *3YCum#PubEdu* for Reclaimable Waste was negative and significant in the fixed-effects model with 2SLS. This negative coefficient once again may have resulted from waste source reduction. Reclaimable Waste consists of left-over motor oil, used oil filters, latex paint, auto batteries, and antifreeze. Public education and outreach programs related to Reclaimable Waste in California have included mass media campaigns to motivate people to recycle. However, there are other kinds of campaigns that can reduce the generation of Reclaimable Waste. For example, CalRecycle promoted using synthetic motor oil, such as polyalphaolefin oil (PAO), instead of conventional oil (CalRecycle 2005). This synthetic oil extends oil-change intervals up to 25,000 miles. CalRecycle also created advertising messages that debunked the “3,000-mile myth” that car owners need to change their motor oil frequently, which was usually unnecessary according to car manufacturers (California Integrated Waste Management Board 2007). These campaigns are likely to result in decreased household consumption of motor oil.

In the Heckman method results, the estimates of *3YCum#PubEdu* for Acid, Base, Oxidizer, and Asbestos Waste were also negative and significant.[10] This suggests that provision of HHW-related education had a negative association with the collection of these waste materials too. This is likely to be the result of source reduction campaigns related to specific HHW materials. A more recent example is Los Angeles County, which is now advising the public on how to reduce the generation of HHW and offering a substitution list of non-toxic cleaning products on the county website (Clean LA, 2016a). Public information regarding Asbestos Waste in California has been disseminated since the years this study covers, through information about types of asbestos and the risks of asbestos exposure to health. Friable asbestos may contain more than 1% asbestos. Example includes acoustical ceiling (popcorn texture), pipe insulation, and blown-on insulation coating. These may cause lung diseases, such as asbestosis, mesothelioma, and lung cancer (DTSC, 2003). This kind of information may encourage households to recycle asbestos material with the help of professional asbestos removal contractors.

[10] The estimate of *3YCum#PubEdu* for Flammable and Poisons Waste was also negative and significant. However, the χ^2 test of the probit model for this waste was not significant so we chose not to include the results from the Heckman method for this kind of HHW in our analysis.

For drinking water quality information in the form of MCL violation counts (*#MCLViol*), the coefficients in the extended model with fixed effects were negative and significant for Reclaimable Waste, Flammables and Poisons, Oxidizers, and Asbestos. The coefficient of *#MCLViolLg* was more rarely significant though – in fact, just for Oxidizers at 0.07 (with 2SLS, $p < 0.01$) and at 0.03 (with Heckman's method, $p < 0.05$). Only about 10% of Oxidizer Waste collected was reused and recycled according to the CalRecycle HHW disposition data in 2004-2012. This again suggested that MCL violation information via mail may have increased the amount of HHW collected, but not necessarily increased the amount of HHW recycled if the HHW was not mostly recycled. More data would have strengthened our estimation capabilities for the various categories because they lacked sufficient observations in some cases to establish significant estimates for the variables.[11]

The coefficients for high school graduate percentage, mean household income, and population in the fixed-effects model and the model with 2SLS were positive and significant for most of the material categories. This suggested that these demographic factors generally had positive associations with the amount of HHW collected, regardless of the material category. The coefficients of population density were mostly not significant, except for the Electronic Waste, with -1.56 ($p < 0.001$) in the 2SLS estimation of the fixed-effects model. This suggested that higher population density was associated with less Electronic Waste collected.

[11] As we noted for the other models, we were not able to estimate all the HHW categories; our models did not fit the data for PCB-containing and Universal Waste very well, so we dropped them from consideration.

2.7. Discussion

We next discuss the main findings related to the influence of household informedness on HHW collection and recycling outputs. Table 2.7 summarizes our hypotheses and the test results.

Table 2.7. Summary of Hypotheses Test Results

NO.	HYPOTHESIS DESCRIPTION	RESULTS	COMMENTS
H1	**Overall Effect of Public Education on HHW Collected Hypothesis:** *HHW-related public education increases the overall amount of HHW collected.*	Partially supported	Positive household informedness elasticity of HHW collection
H2	**Category-Specific Direct Effect of Public Education on HHW Collected Hypothesis:** *HHW-related public education directly decreases the amount collected for a few HHW materials that have non-hazardous substitutes.*	Supported	Negative and significant coefficient in Model 1, extended by material categories for Reclaimable, Acid, Base, Oxidizer, and Asbestos Waste
H3	**Indirect Effect of Public Education on Overall HHW Recycled Hypothesis:** *HHW-related public education indirectly increases the overall amount of HHW recycled.*	Supported	Positive and significant coefficient in Model 2's *HHWRecQ* equation
H4	**Effect of Environmental Quality Information on Overall HHW Collected Hypothesis:** *Information on low environmental quality in a county increases the amount of HHW collected when households perceive there is a problem.*	Supported under certain conditions	Positive and significant *#MCLViolLg* (MCL violation count information sent by direct mail) in Model 1

Our Overall Effect of Public Education on HHW Collected Hypothesis (H1) in California was only partially supported. The HHW public education variable was not significant in Model 1. This was probably because this model did not adequately capture the variability in the waste material types, the negative effects from waste source reduction efforts, and the bias from local governments' purposeful actions.[12]

[12] An anonymous reviewer suggested that we should model the relationship between the *probability of recycling HHW* and household informedness. We modeled this using a *generalized linear model* (GLM) with a logit link and a quasi-binomial distribution. We used the proportion of the amount of HHW recycled relative to the HHW collected in pounds as the dependent variable. *3YCum#PubEdu* was not significant so this model also may not have been able to capture the variation in the effects of the material categories. I also did not capture the negative effects from waste source reduction measures.

Nonetheless, the estimated household informedness elasticity value of HHW collection outputs for HHW public education derived from Model 2 was positive and significant at the 10% level. Although this value was calculated based on a system of equations that held the amount of HHW recycled constant, still it partially supported Hypothesis 1.[13]

HHW-related campaigns and outreach also provide information about alternative non-hazardous household products and better practices that can reduce the generation of HHW. We obtained support for the Category-Specific Direct Effect of Public Education on HHW Collected Hypothesis (H2), suggesting that HHW-related public education can decrease the amount of HHW from household products with non-hazardous substitutes. Our extended analysis by material category showed that HHW-related public education was negatively associated with the amount of Reclaimable, Acid, Base, Oxidizer, and Asbestos Waste collection. The negative association suggested that media campaigns and information related to synthetic oil use as an alternative to conventional motor oil and alternative household products without these hazardous materials had a stronger influence on households to reduce waste generation than to participate in collection programs. We also wonder if the public did not necessarily see these as true substitutes, regardless of the body of knowledge that would show that they are, and yet we see evidence of this in the motor oil example. Initially, the general recommendation was to change a car's motor oil every 3,500 miles, but now it is more widely believed that a car doesn't need

[13] Additionally, when we performed the analysis for the different material categories, we found a positive association between HHW-related public education and the amount of PCB-containing and Universal Waste collected. But these relationships occurred in models for which our confidence in their overall fit was quite low (to the point that we have not reported the details of the results.) So it is not appropriate, in our view, to suggest that HHW-related public education increased the participation of households in HHW collection programs for household waste in these material categories. A majority of households have Universal Waste, and a lot of public environmental education probably focused on it.

its oil changed for 7,000 miles. This may account for the drop in waste generation over time as less motor oil would have been necessary. Due to the difference between synthetic and conventional motor oil, consumers may have been slower to switch to more costly synthetic motor oil. Thus, synthetic motor oil may be a technical substitute for conventional motor oil, but it has characteristics that make it less-than-best. This may explain our results.

These results showed that the impact of HHW-related public education was multifaceted; it seems to have had a positive effect on the amount of HHW collected, but it also may have had a negative effect in some circumstances due to source reduction measures. These countervailing effects may have been working simultaneously. Whether the positive or negative effect was stronger depended on the HHW material type. Some household products can be substituted easily with other products with less hazardous material; some cannot. It also depended on the maturity of the collection program. The positive effect may have been most pronounced in the early stage of the collection program and the source reduction effect may have come afterward. It may have taken less time for local governments to encourage households to deliver their waste to facilities or events than to persuade them to change the selection of their household products or to change their consumption behavior. [14]

Our data analysis supported the Indirect Effect of Public Education on Overall

[14] We further note that the *theory of planned behavior* (Ajzen, 1991) has been used in studies related to public communication campaigns (Wood, 2006; Largo-Wight et al., 2012) to explain the gap between one's intent to behave some way and then doing it. According to the theory, the success of HHW public education to influence households' behavior in disposing of HHW properly should be determined by *perceived behavioral controls*, such as disposal convenience of HHW, or perceived ease of HHW delivery to recycling facilities. Our model did not touch on this, since we did not conduct a field survey in this work.

HHW Recycled Hypothesis (H3) that HHW-related public education had some influence on the overall amount of HHW recycled. We used a system of equations to model HHW collection and recycling simultaneously to estimate the indirect effect of HHW-related public education on the amount of HHW recycled despite the unobserved source reduction practices. This result indicated the importance of HHW-related public education in maximizing the proportion of recycled HHW from the total amount of waste collected in HHW collection programs.

There was some support for the Effect of Environmental Quality Information on Overall HHW Collected Hypothesis (H4) but only under limited conditions. This hypothesis is about the effect of information on low environmental quality in a county. We found that the MCL violation information had a positive association with the amount of HHW collected, but only when it was delivered to households via direct mail. Surprisingly, we found that when people perceived the drinking water quality to be low, the lower was the amount of HHW collected in the county – at least in models without time lags. This suggested that the direct channel for environmental quality information may have had more impact on household environmental awareness than the indirect channels, such as public notices and newspapers.

Simply relying on public media to convey the information may not be as effective as delivering the information through a more direct and interpersonal channel in influencing public behavior though (Nixon and Saphores, 2009). And there is also the possibility that there are lag effects from the time of awareness to actions to recycle and improve environmental quality. Our research design did not consider this. Also, the effect of the MCL violation information depended on the number of violations; we found that there was more of an impact on HHW collection and recycling outputs when the violation count changed greatly.

The findings related to the impact of household informedness on HHW collection may have varied not only due to the waste material category but also due to other unobservable factors, such as the diversity of California's population. The state has long been viewed as ungovernable due to its size and diversity. Over 200 initiatives to sub-divide California into smaller states have been launched, and these initiatives began soon after the state entered the union. A new initiative was launched in 2016 to subdivide California into nine different states. The spillover effect of informedness from one county to its neighbors is another factor that is difficult to observe. We will investigate these issues in future research by creating a geospatial and geotemporal research design.

In addition to the findings related to household informedness, we learned that the socioeconomic characteristics of the counties in California were an important determinant of the HHW collection and recycling outputs. Our model estimates showed that education level, household income level, and population were positively associated with HHW collection and recycling outputs, as we expected. On the other hand, our model estimates showed a negative association between population density, and HHW collection and recycling outputs, respectively. This is also not surprising though because households in high population density areas may have more opportunities to dispose of HHW illegally. So they may have been less motivated to participate in HHW collection programs.

We also calculated the household informedness elasticity of HHW collection and recycling output. Analogous to price elasticity of demand, informedness elasticity is useful to gauge the responsiveness of households in terms of HHW collection and recycling outputs as more educational and environmental information becomes available to them. This can help local governments and waste managers to assess how much more effort or costs need to be invested in improving household informedness related to HHW and the environment to achieve the most household participation and desirable output in collection programs.

The household informedness elasticity of HHW collection outputs from HHW-related public education consists of two components: the direct effects of HHW-related public education on HHW collection outputs (holding the amount of HHW recycled constant) and the indirect effects on HHW recycling output. By holding the amount of HHW recycled constant, we attempted to isolate the effects from source reduction. Although there was uncertainty in the elasticity estimates, we found a higher estimate for the positive effect of HHW-related public education on HHW recycling compared with HHW collection. This confirmed our conjecture about the negative effect from waste source reduction activities related to HHW collection. This also implied that measuring the effect of HHW public education based on the amount of HHW collected only – without considering the source reduction effect – may underestimate the impact.

For California during the 2004 to 2012 period, we found that the HHW collected and recycled amounts were *informedness inelastic*. The responsiveness of HHW collection outputs to the differences in household informedness via HHW-related public education and environmental information seem to have been relatively low. Informedness via HHW-related public education and environmental information was inelastic probably because many households in California already were well-informed about HHW before 2004 so that more campaigns about HHW did not result in more HHW collection.[15]

2.8. Conclusion

We assessed the role of household informedness in the collection and recycling of HHW outputs using econometric analysis. We also evaluated the effectiveness of HHW-related public education and environmental quality information in influencing households to participate in collection programs and to improve their pro-environmental behavior by decreasing their generation of HHW. After estimating the effects of household informedness, we introduced a new impact estimator – *household informedness elasticity of HHW collection and recycling outputs* – that is useful to gauge the responsiveness of HHW collected and recycled as more educational and environmental information is available.

We demonstrated the transformation of data collected from various public sources into policy analytics findings that give insight into the mechanism for the impact of household informedness in waste management, particularly HHW. By understanding this mechanism, local governments and waste managers can devise effective strategies and policies related to public information that promote pro-environmental behavior and encourage households to manage their waste better. Implementing these strategies will enhance participation in delivering their existing HHW and mitigating the generation of new HHW.

The empirical models we used in this research were useful to capture the relationships between household informedness and the quantity of HHW collected. We

[15] The varied effects of HHW-related public education across different material categories may reflect the disparate levels of informedness related to different HHW material categories. Households would have benefited from more information about Reclaimable and Asbestos Waste, which has been collected in California since 1992. Universal Waste was completely banned from trash in 2006. So investing more effort and cost in promoting such recycling would have improved HHW collection and recycling in this category relatively more too.

note the limitations with the linearity assumption of the estimation models and the measurement approach that we adopted for the estimation of the impacts of informedness. We may be able to improve the estimation models by adding non-linear relationships in future research, but all signs suggest that we will need more data to make this worthwhile.

We measured the extent to which the informedness level was influenced by HHW public education with the number of 3-year cumulative projects with an educational campaign on HHW. It is likely that the quality of any individual educational program may differ from another, but we expect that, on average, there will still be a similar influence. With better data, we can estimate their effects more accurately.

Although we included estimates of household informedness impacts on HHW collection by material category, we did not perform a detailed analysis for each of the specific HHW materials. Each HHW material category may have different educational campaigns, hazardous risks, and regulations. So our estimates of the impacts of household informedness may be more applicable to HHW in general, but may not be as effective for a specific material category model-wise, such as PCB-containing and Universal Waste.

Further, our models can be refined and expanded to develop even more targeted policy analytics for waste management that involves households, local governments, and other stakeholders. But, unmistakably, this research highlights the challenges facing policy-makers in creating programs that improve waste management and recycling. This research contributed a novel approach to quantifying the impact of household informedness in a way that may be useful for policy-makers in assessing the costs and benefit of their educational campaigns and information programs related to HHW at the county level. This kind of assessment will help state-level waste managers and governments in planning the appropriate information policies and strategies to increase household informedness for collecting more HHW generated by households and reduce this waste as much as possible at its source. This will prevent HHW from contaminating our land and water so that we all can enjoy living in a healthy and sustainable environment that is free from hazardous waste.

Chapter 3. Geospatial Policy Analytics for Household Hazardous Waste Collection

3.1. Introduction

Improper disposal of *household hazardous waste* (HHW) causes hazardous substances to contaminate the environment. When hazardous substances are released into it, they can pollute the groundwater, the main source of our drinking water (U.S. EPA, 2015a). This causes adverse health effects for people living in the vicinity of the contamination. Thus, it is crucial for municipal and regional governments, in collaboration with producers and waste management service providers, to effectively manage HHW collection and disposal.

Government grants for HHW management, for example, programs in California (CalRecycle, 2016) and New York (NYS Dept. of Environmental Conservation, 2017), are also crucial to communities because they provide necessary funding for projects that establish or expand HHW collection and recycling drop-off facilities, curb-side and take-back programs, and collection events. Assessing the causal effects of grants on the HHW collection activities will help policy-makers to evaluate whether the dissemination of grants has resulted in improved collection of HHW, and made a positive impact on the quality of the environment where we all live.

Previous studies have shown that the patterns of waste collection vary with locations. Examples include the recycling of electronic waste in the rural areas of China (Tong and Wang, 2004); the collection of municipal solid waste in an island city there (Zhang et al., 2014); and waste recycling in the U.K. too (Abbott et al., 2011). Additionally, pollution or other environmental problems caused by improper disposal of hazardous waste may spread over the geographical in which this occurs.

So applying geographical data analytics approaches is appropriate to provide a spatial perspective on key environmental issues, as in studies conducted on pro-environmental tourist travel (Barr and Prillwitz 2012), environmental issues with polluting-generating plant relocation (Liu 2013), and geographic inequality in pollution mitigation (Bakhtsiyarava and Nawrotzki 2017). Similarly, in analyzing the effects of grants on HHW collection output, the spatial dimension should be considered because environmental sustainability-related activities in a locality may encourage similar kinds of beneficial activities nearby.

Considering the spatial dimension of waste management, this research also investigates the *spatial effects of pro-environmental activities*. This term is defined as the influence of pro-environmental activities, such as HHW collection, government announcements of new recycling programs, and news of advancing performance of recycling, from close-by counties or regions. Such effects are likely to arise under two conditions. First, the participation of households is related to the extent to which they exhibit pro-environmental behavior, which is strongly influenced by what is happening around them (Agovino et al., 2016). Second, strategic interactions among local governments may encourage pro-environmental activities to a greater extent when they cooperate in achieving high environmental quality (Brueckner, 2003).

Impact evaluations that identify the causal effects of policies in spatial terms are in short supply due to data availability issues, the absence of explicit randomization, and other practical barriers (Gibbons et al., 2014). Establishing causal relationships is critical in assessing environmental policy to obtain an unbiased evidence base with better internal validity (Ferraro, 2009). When carrying out a randomized controlled experiment is not an option, the available identification strategies include research designs to address selection for unobservable factors that are present in the setting (Gibbons et al., 2014). The selection of the strategies depends on the sources of variation in the variables associated with the treatment and in the data overall (Baum-Snow and Ferreira, 2015).

Given the nature of the observational data that we use in this research, we employ a spatial panel data model that explicitly consider unobservable, time-invariant effects from neighboring counties that may influence HHW collection activities in another one that is nearby. HHW grants were not randomly awarded to waste agencies in the counties, so an instrumental variables (IV) method is applied to isolate the unobserved factors that determined the amount of grant funding awarded to specific counties. To our knowledge, this research is the first empirical study that attempts to model the effects of HHW grants on HHW collection outcomes and by explicitly measuring the spatial spillover effects from the pro-environmental activities in nearby geographic areas. Besides employing econometric methods, we perform data tests and robustness checks to achieve causal inference.

Our empirical research uses HHW collection and demographic data in California due to the state's diverse geography and demographics. HHW has been banned from trash in California since 2006. California's Department of Recycling (CalRecycle) mandated the waste management agencies in the state to report on HHW collection and disposition activities annually. Each waste agency manages HHW programs in the counties that it covers. At the same time, we observed that there was some collaboration among the counties in managing HHW. For example, Calaveras County developed a "medical sharps" collection strategy with the Central Sierra Sharps Coalition that involves four counties: Alpine, Calaveras, El Dorado, and Tuolumne Counties (CalRecycle, 2016b). Such programs need to be considered when estimating the impact of HHW-related policies and strategies on HHW collection activities.

In this study, we model the spatial effects of HHW grants on HHW collection. The effects are then quantified to create a meaningful policy analysis. Our goal is to provide impact assessments of waste collection beyond associational results and findings. So we ask: (1) What mechanisms involving spatial dependencies are in operation across counties and regions? (2) Are there any pro-environmental locational effects of HHW collection activity among neighboring counties? (3) What are the impacts of HHW grants on the amount of HHW collected considering spatial dependencies?

Besides addressing these research questions, understanding the impact evaluations can offer insights into what drives the amount of HHW collected so that policy-related questions can be answered. They include: How much do HHW grants awarded to counties in a region generally influence their HHW collection performance? Is it possible to estimate the differential effects of such awards across different geographic and demographic environments? Estimating causal effects of HHW grant using observational data while considering spatial effects from the pro-environmental activities from close-by areas are the main contribution and goal of this research. This results in an innovative contribution in applied geography research.

3.2. Theoretical Insights

In the standard economic theories, individual households make choices to maximize their utility or well-being under the constraints they face. This study broadens the theoretical framework to analyze the HHW collection activities to include for theoretical insights from other issue areas in the social sciences that can explain environmental behavior, including social dilemmas, pro-environmental behavior, and its geographic contagion effects. These insights led us to establish a model that represents the causal relationships between the HHW collection outputs and the HHW-related policies, such as HHW grants, with consideration of the spatial effects from close-by areas.

The success of HHW collection programs highly depends on households' participation in separating and collecting HHW. With the participation of only a few households, the local government is less likely to be able to divert the hazardous materials from contaminating the environment. When the environment is contaminated by HHW from nearby counties, even the households that participated in the HHW collection program are not guaranteed to be free from environmental contamination because it can spread through land and groundwater across county boundaries. Everyone in the vicinity will suffer if most households do not separate and deliver their HHW to be recycled or processed properly. This situation is recognized as a social dilemma in maintaining good environmental quality (Hage et al., 2009).

To resolve this kind of social dilemma, cooperation among households and local governments of neighboring counties is required. This cooperation leads to spatial spillovers of HHW collection activities among nearby households and local governments. As the spatial spillovers can cross administrative boundaries so we can observe the spillovers at the county level as well.

The cooperation of households will happen if households have exhibited prior pro-environmental attitudes and behavior, in which they weigh the long-term societal and environmental consequences of their decisions (Vugt et al., 1995). Similarly, households with good pro-environmental behavior will be willing to separate their HHW and dispose of it properly because they are aware of the danger of hazardous material contamination to the environment and to people's health who live near the contamination.

Pro-environmental behavior is subject to geographic contagion due to *socio-spatial transmission effects* (Truelove et al., 2014). In a province-level study in Italy, Agovino et al. (2016) found that pro-environmental behavior (proxied by the rate of waste separation prior to collection) in a province can be influenced by the behavior of the nearby provinces. Specifically, proximity to regions with good pro-environmental behavior in one region may positively influence neighboring regions with worse pro-environmental behavior. Similar to recycling of differentiated waste in Italy, socio-spatial effects in HHW collection and recycling activities can be viewed at the province or county level. So, HHW collection activities from households of nearby counties should have *positive spatial spillover effects* on the collection activities in a county when households cooperate to address environmental pollution.

Besides the pro-environmental behavior of households, the spatial effects may happen at the local government level as well. In public economics, the decision of a jurisdiction may be affected by the decisions undertaken in neighboring jurisdictions due to the interaction among the local governments (Brueckner, 2003). The interaction among the local governments located in the counties that nearby to each other may facilitate resource transfers or collaboration in facility improvement projects. These interactions are motivated by the goal to achieve higher environmental quality that will be achieved when most neighboring counties manage their HHW properly too. As an example, local governments in 22 rural counties in California formed the Environmental Services Joint Powers Authority (ESJPA, 2017) to provide regulatory advocacy and technical support related to recycling and hazardous waste management.

Besides pro-environmental behavior, according to the theory of planned behavior (Ajzen, 1991), households may not cooperate in diverting HHW if the tasks are perceived to be difficult, especially if HHW collection and recycling facilities are too far away or inconvenient to access. So, a local government's role in providing the necessary HHW facilities and programs is very crucial. The establishment of HHW programs, in some regions, is supported by state governments through HHW grant funding. As more new facilities become available and existing facilities are improved due to the projects funded by these grants, households will be more likely to participate in waste collection programs due to their increased awareness of them and their accessibility. More HHW can be collected, recycled, and most importantly, diverted from polluting the environment. So, HHW grant should have positive effects on the amount of HHW collected.

3.3. Context and Data

California is selected for our study due to its diverse geography and demographics. As we can see in Figure 3.1 (left), based on cultural and political differences, the counties in California can be divided into roughly two main regions: north and south.

Figure 3.1. California Geography and Regions

Source: WorldAtlas.com (2017)

The north region is comprised of 48 counties and the south region includes 10 counties. The central region is the sub-region of the north region. It includes Fresno, Kings, Madera, Merced, Monterey, San Benito, Stanislaus, Tulare, and Tuolumne counties (Kent, 1917). In the north region, Sacramento Valley is surrounded by the Coastal Mountains, Klamath Mountains, and the Cascade Mountains. The Coastal Mountains are fronted by the beaches of the coastline that faces the Pacific Ocean. In the north and central region, the San Joaquin Valley is positioned between the Coastal Mountains and the Sierra Nevada Mountains. In the south region, the Mojave and the Colorado Deserts cover most of the southeast area (World Atlas, 2017). As the most populous state in the U.S. since 1962, California: consisted of 38% Caucasian people in 2015; had a 54.3% owner-occupied housing unit rate in 2011 to 2015; and had a high proportion of well-educated people with 81.8% high school graduates in 2011 to 2015. Its median household income was $61,818 in 2011 to 2015 (U.S. Census Bureau, 2015).

Geospatial data for California, was acquired from Version 2.8 of GADM (2015), includes the boundaries of 58 counties. For the map projection, we used North American Datum of 1983 (NAD 83) that has been officially adopted by California (Public Resources Code, 2005). Implemented in 1986, NAD 83 is the horizontal control data for the United States, Canada, Mexico, and Central America, in which the system is constrained to a geocentric origin based on the adjustment of 250,000 points including 600 satellite Doppler stations (National Geodetic Survey, 2009). CalRecycle oversees waste management in the state since 2010; previously, it was the California Integrated Waste Management Board (CIWMB) established in 1989.

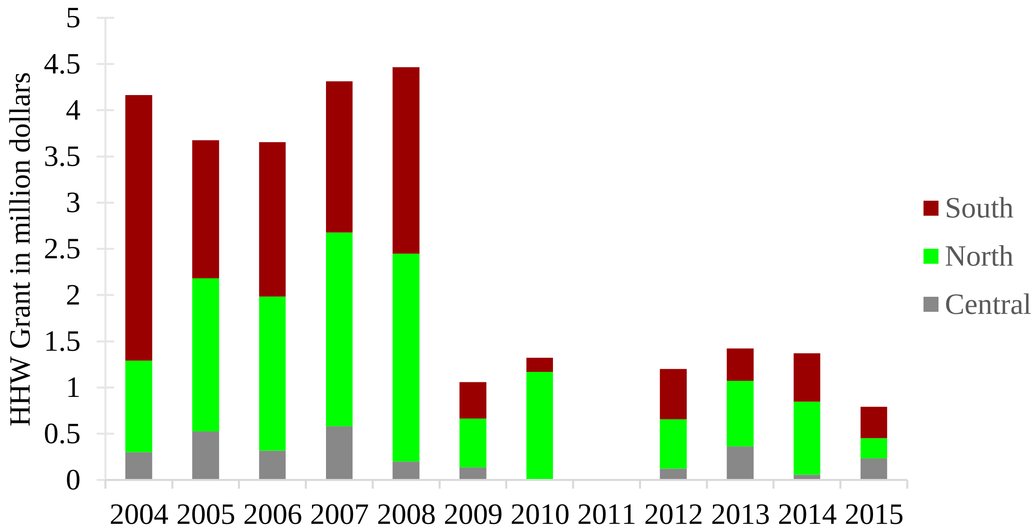
We collected HHW collection data from CalRecycle Form 303 that contains historical HHW data from 2004 that was submitted by public agencies responsible for HHW management annually by October 1 (with the reporting period from July 1 to June 30) annually (CalRecycle, 2014a). Although the waste data is at agency level and contains details of material types, we aggregated the total amount of county-level HHW data, normalized by the county population.

The demographics data include population density, mean household income, and percentage of high school graduates. They were collected from the American Community Survey (U.S. Census Bureau, 2015) for the years 2005 to 2015[16]. The data do not include all counties in California so it limited the space-time panel data to cover only 39 counties. We also use taxable sales as a proxy for overall economic activity in the state. The data were collected from the California State Board of Equalization (2015) from 2004 to 2015.

[16] Demographic data for 2004 were backward extrapolated by using the annual growth rate calculated from historical data from 2005 to 2012.

In California, HHW grants have been awarded annually to local governments, cities, counties, or waste management agencies to establish or expand HHW collection or recycling facilities for enhancing the local environment's sustainability (CalRecycle, 2016b). Grants are awarded every July, which is the beginning of the HHW reporting period each year. Figure 3.2 shows the grant amounts awarded from 2004 to 2015 to the 39 counties included in our study. The amount was around $3.5 to 4.5 million before 2009 and $1 to $1.5 million from 2009 on. The funding reduction coincides with the January 2010 transfer of waste management responsibilities to CalRecycle from CIWMB.

Figure 3.2. HHW Grant Amounts Awarded to 39 Counties in Our Study, by region, 2004 to 2015



Notes. No regular HHW grant was awarded in 2011. The funding was allocated to a one-time grant to support a safe, convenient and cost-effective infrastructure for collecting and disposing of home-generated medical sharps waste (CalRecycle, 2013). The awarded amount was not provided by the CalRecycle website.

Since the term of the grant is for three years, we use the *cumulative grant award over three years* as the grant variable in our analysis. We compare this variable with the HHW collection density for each Californian region and its county type using boxplots (See Appendix A). 2013 Rural-Ruban Continuum Code (RUCC) published by the U.S Department of Agriculture, Economic Research Service (2013) is used to classify the county by their population size, degree of urbanization and adjacency to a metro area. The boxplots show somewhat similar pattern between the three-year cumulative grant variables with the HHW collection density variable.

We aggregated all datasets by county and year. The definitions and the descriptive statistics for the variables used in our study are presented in Tables 3.1 and 3.2.

Table 3.1. Variables for Counties and HHW-related Observations

VARIABLES	DEFINITIONS
EduHS%	% population over 25 with high school diploma
Density	County density (in 000s of square feet per capita)
HHInc$	Mean household income in county (US$ 0,000s)
TaxSales$	County taxable sales (US$ / person)
3YCumGrant$	3-year cumulative HHW grant(s) awarded (US$ millions / person)
CollD	Quantity HHW collected (pounds / person)

Table 3.2. Description of the County-Level Variables

VARIABLES	MEAN	STD. DEV.	MEDIAN
EduHS%	82%	8%	85%
ln (Density)	5.58	1.43	5.20
ln (HHInc$)	11.21	0.26	11.20
ln (TaxSales$)	2.61	0.25	2.63
3YCumGrant$	$0.44 / person	$0.90 / person	$0.10 / person
CollD	3.79 pounds / person	3.53 pounds / person	2.63 pounds / person
Notes. Obs: 468, 39 counties, 2004-2015. Some variables computed using data from multiple sources.			

3.4. Estimation Approach

The estimation that we conduct to establish causal relationships is challenging due to two main reasons. First, spatial dependencies exist in HHW collection activities. This is due to the effects of pro-environmental behavior among households and interactions among local governments. Ignoring such spatial dependencies may result in biased estimates, as their effects spill over into the observation of HHW collections by location and by year.

Second, although the HHW grant awards were pre-determined before the beginning of the HHW collection survey, the grants were not awarded randomly to the local government or waste agencies. In California, the eligible local governments and waste agencies submit their project proposal and then they are selected on a competitive basis. The grant applications are reviewed based on criteria such as the need for the funding, the work plan, and the budget. Additional discretionary criteria points are also given to projects in rural areas, small cities, or underserved populations and agencies that have not received any grants in the last two years before the application (CalRecycle, 2016b). Thus, the HHW grants variable is *endogenous* due to the unobserved factors that affect the amount and the decision to award the grants to particular counties.

Additionally, there may be correlations with HHW collection in the previous years that are unobservable (i.e., *serial correlation in the error term*). Although serial correlation affects the efficiency of the estimators, it will not affect their unbiasedness and consistency.

Our research approach takes into consideration of these challenges. See Appendix Figure B1 for an overview of the methods used in flowchart form. We first develop a baseline spatial panel data model that explains the relationship between HHW collection and grants. A set of Lagrange multiplier tests (Baltagi et al., 2007) are employed to test the model for serial correlation, spatial autocorrelation, and random effects. In the random effects specification, the unobservable time-invariant county effects are assumed to have homoscedastic variance and are orthogonal to each of the explanatory variables. To test the validity of this assumption in our panel data, we use the Spatial Hausman test that compares the random and fixed effects estimators (Mutl and Pfaffermayr, 2011).

After confirming the presence of county-level random county effects, serial correlation, spatial dependence in the error terms of the model, and the specification assumptions, we ran the model using random effects estimators and the *instrumental variable* (IV) method to handle the endogeneity issue with the *Grant* variable, spatial lag dependence, and the error term structure.

Different spatial weights used in the model may result in different estimates (Corrado and Fingleton, 2012). So, we performed sensitivity analysis with various spatial weight matrix. To further check the internal validity of the estimates, we investigate whether there were other plausible alternative explanations for the changes in the HHW collection outputs.

3.4.1. Model Specification

Our panel data model has spatial lag dependence and permits county effects, in which HHW collection in a specific year is a function of related grant funding:

$$CollD_{it} = \alpha + \lambda \sum_{j=1}^{N} w_{ij} CollD_{jt} + \gamma 3YCumGrant\$_{it} + \beta x_{it} + \mu_i + e_{it} \quad (3)$$

Here, i is the index for county; j is the index of the other county; N is the number of counties; t is the index for year; $CollD_{it}$ is the HHW collection density normalized by the county population (in pounds per person); $3YCumGrant\$_{it}$ is the amount of HHW grant normalized by the county population (in dollars per person); x_{it} is a vector of the control variables; w_{ij} is a pre-specified spatial weights matrix for HHW collection as in the spatial autocorrelation analysis; and λ is the associated scalar parameter of the spatial lag of *CollD*. Also, μ_i is a vector of time-invariant county-specific effects; e_{it} is the idiosyncratic errors; and α_i are the intercepts.

For the control variables, we use county demographic variables, which include mean household income (*HHInc$*), population density (*Density*), and education level (*EduHS%*). These variables have been used in previous empirical research in recycling and HHW management, such as Sidique et al. (2010), Abbott et al. (2011), and Lim-Wavde et al. (2017a). Better educated households are expected to be more aware of the risks of HHW so they will be motivated to separate and recycle their household waste. Households with higher incomes have time and access for participating in HHW collection programs or deliver their waste to HHW facilities. In contrast, although previous empirical research on recycling showed that population density was positively associated with recycling (Sidique et al., 2010), other studies (Kinnaman and Fullerton, 2000) found that it was negatively associated with the amount of HHW collected. This is because lack of space may have held up households from separating waste before recycling or delivering it to the appropriate facilities.

The spatial weight matrix, w_{ij}, defines the relationships among the features in the dataset.[17] The State of California measures about 560 miles from east to west, and about 1,040 miles from north to south. It also has diverse geography and land areas. Northern California consists of counties with smaller land areas and farms, forests, mountains, and valleys. Southern California, in contrast, has counties with larger land areas, including desert expanses, coastal cities, and suburbs. If contiguity-based weighting were used, then some counties would have many neighboring counties, while others would have relatively few. Moreover, HHW collection programs in one county may affect several other nearby, not only those bordering counties that share the same boundary.

To take this observation into account, the research design of this work applied an *adaptive distance-based weight matrix*. This was calculated using a *bi-square*

[17] There are three types of weights. *Contiguity-based weights* only consider the other counties that share the same boundary as their neighbors. *Distance-based weights* are specified using a function of the distance separating the counties; the neighbors can be determined using the *k*-nearest neighbor criterion or distance bands (or thresholds). *Kernel weights* combine the distance based thresholds together with continuously-valued weight functions, such as bi-square, tri-cube, exponential, or Gaussian functions (Lloyd 2010). We did sensitivity analysis by calculating the weight matrices using these functions, and the bi-square function supported detection of more counties in spatial clusters compared to other functions.

distance function with an *adaptive distance limit*, but a fixed number of neighboring counties. This ensures there is the same number of neighboring counties for both when the spatial weights for a pair of counties are calculated. In addition, the weight matrix was row-standardized with diagonal 0, in which the rows of the neighbors matrix must sum to unity.

The bi-square distance function is discontinuous and excludes observations beyond some distance (*b)*. In addition, the weights decrease as the distance between the assigned reference points (d_{ij}) increase.[18] The *distance between counties* is calculated by using *population centroid coordinates*, for which the coordinates of the county seats are used. Compared with the possible use of *geographic county centers* for this analysis, the application of *population centroids* is important for capturing spatial autocorrelation and the uneven distributions of the population in counties of the waste collection. The latter is more appropriate to support research inquiry at the county level with respect to household patterns of HHW collection and recycling.

Before estimating the model, we tested the panel data for spatial autocorrelation, serial correlation, and random effects using the *joint and conditional Lagrange multiplier* (LM) tests (Baltagi et al., 2007). The results are reported in Table 3.3. The joint conditional test was rejected; this indicates the existence of spatial or serial correlation or random county effects. The C.1 and C.2 conditional tests were also rejected so there may be spatial error and serial correlation.

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[18] The function is: $w_{ij} = \left\{ \left(1 - \left(\frac{d_{ij}}{b}\right)^2\right)^2 \quad if \ |d_{ij}| < b, \right.$ and 0 otherwise (Gollini et al., 2015). For a fixed number of neighbors, we needed a large enough sample size to calculate the spatial autocorrelation.

Table 3.3. Baltagi, Song, Jung and Koh joint test results

TEST	LM	NULL HYPOTHESIS
J Joint	749.35 ***	No spatial or serial error correlation and no random region effects
C.1 Conditional	9.18 ***	No spatial error correlation allowing the presence of both serial correlation and random region effects
C.2 Conditional	57.27 ***	No serial correlation allowing the presence of both spatial error correlation and random region effects
Notes. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.		

3.4.2. Generalized Moments Estimation

We employ the *generalized spatial two-stage least squares* (GS2SLS) estimation procedure proposed by Kelejian and Piras (2017). The procedure involves several steps. *Generalized moments* (GM) estimators are first defined based on the related moment conditions to estimate the variance components for the general spatial panel model (Kapoor et al., 2007). In this step, we select the GM estimators that take into account all of the moment conditions and apply an optimal weighting scheme. Given the estimates of the variance components, the model can be transformed to account for spatial error lags and the variance-covariance matrix of the error terms. Since the spatial lag of the dependent variable (*CollD*) is endogenous, we implemented an IV procedure as in the study by Baltagi and Liu (2011) using instruments proposed by Kelejian and Prucha (1998). The coefficient estimates were then estimated using a *feasible generalized least squares* estimator (Wooldridge, 2002).

To solve the endogeneity issue with HHW grants variable, we include an IV that is correlated with HHW grants but not directly correlated with the amount of HHW collected or other unobservable (i.e., error term). For this purpose, we use a binary variable (*D_CalRecyle*) that are set to 1 from year 2009 onwards. This variable indicates the change of the total amount of HHW grants (illustrated in Figure 3.2) when CalRecycle took over the waste management responsibilities in January

2010. In addition, the county-level taxable sales amount per capita (*TaxSales$*), which represents the economic activity in the county, is also used as an IV because counties with high economic activity may need fewer grants than those with low economic activity.

3.5. Estimation Results

Table 3.4 summarizes our findings from the GM estimation for the effects of HHW grants and spatial spillover effects on HHW collection outputs.

Table 3.4. Model Estimation Results

VARIABLES	RANDOM EFFECTS		SPATIAL RANDOM EFFECTS	
	COEF.	SE	COEF.	SE
Grant γ	1.70***	0.54	1.27**	0.54
λ	--	--	0.65**	0.27
α	-45.58***	14.11	-36.07***	13.78
EduHS% β_1	10.50***	4.36	9.73**	3.95
ln *(HHInc)* β_2	3.96***	1.38	2.96**	1.34
ln *(Density)* β_3	-0.80*	0.38	-0.76**	0.33
Pseudo-R^2	93.4%		92.7%	
$Corr^2$	--		29.3%	
SSE	387.6		423.7	

Notes. Baseline model: random-effects; dep. var.: *CollD*; 468 obs. (39 county x 12 years). IV for *Grant: D_CalRecycle*, ln(*TaxSales$*). Spatial weights based on adaptive bi-square distance function with 30 nearest neighbors. Spatial Hausman test: $\chi2 = 5.15$, $p = 0.27$); so cannot reject null hypothesis that random effects estimator is consistent. *Pseudo-R^2* = 1 – (variance of model residuals / variance of HHW collection density); *$Corr^2$* = square of correlation between HHW collection density predicted by model and empirical HHW collection density. Difference between *pseudo-R^2* and *$Corr^2$* indicates how much variation is explained by fixed or random effects (Elhorst, 2014). Spatial errors not considered. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The "Random Effects" column reports estimates of the random effects model ignoring the spatial dependence while the "Spatial Random Effect" column coefficient reports the estimates of variable parameters in the spatial random effects model.

The coefficient of HHW grant γ was positive and significant ($p < 0.1$) in both the random effects and spatial random effects estimates. These findings indicate that all else equal, the HHW grants had positive effects on HHW collection density.

The effect estimate was lower after spatial dependence was included in the model though. This means that if the spatial effects were excluded, the effects of HHW grant funding on the HHW collection output would have been overestimated. After isolating the influence from the neighboring counties, we found that $1 more in the grants awarded to a county led to ~1.3 pounds more HHW collected per person in the county ($p < 0.05$).

The coefficient of the spatial lag for HHW collection output, λ, was also positive ($p < 0.01$), which confirms the presence of the positive spillover effects of HHW collection activities from the nearby counties in California. In other words, the pro-environmental activities in a county appear to have been positively influenced by their nearby counties.

As expected, the coefficient the county characteristics had the same sign in both estimations. The education level β_1 and household income variable β_2 were positive and significant, whereas the coefficient of population density β_3 was negative and significant. So higher education level and household income lead to more amount of HHW collected in a county. Based on the magnitude of the coefficients, the most important control variables is the education level. However, higher population density discouraged household to dispose of HHW appropriately. This finding is consistent with our previous study (Lim-Wavde et al., 2017a).

3.6. Data Tests and Robustness Check

To establish causal relationships for the relationships among HHW grant, collection outputs, and spatial effects, we used a spatial panel data model with random effects estimators to address spatial correlation issues and unobserved county effects. Instrumental variable procedure was also employed to address the endogeneity issue of the treatment variable: HHW grants. However, there remain threats to *internal validity* of the causal inference of HHW grant (i.e., whether the causal effects are valid for the population).

First, the HHW grants during our study period were discretionary grants in which CalRecycle selected awardees based on their merit and eligibility. The selection scheme could bias the results though. Some counties may have a higher chance of getting a grant than the others. The IV procedure may have addressed such bias from unobserved confounding factors, but it may not have addressed selection bias completely. To check this condition, we performed some *t*-tests to compare the counties that received the grant or did not receive a grant that year (see Table 3.5). Their results indicate that counties that received grants had higher density and economic activities on average. During our study period, for example, Los Angeles, Riverside, and Sacramento were awarded more often than the others.

To overcome this issue, many studies employ *Propensity Score Matching* (PSM). In this research, PSM is useful to match data observation for the treated counties with the untreated ones based on known characteristics of the counties. But, the standard PSM approach is not useful for our case because the counties were awarded the grants in different years and at different frequencies. Only Nevada county was not awarded the grants at all during our study period. Consequently, the estimated effects of the grants may be biased downward because counties with high population density and economic activities had low collection density (normalized by population).

Table 3.5. *t*-test Results for Difference in Means

AWARDED GRANT	MEAN OF LN (HHINC)	MEAN OF EDUHS%	MEAN OF LN (DENSITY)	MEAN OF LN (TAXSALES$)
No	11.21	0.82	5.47	2.58
Yes	11.21	0.82	5.77	2.64
t-test *p*-value	0.90	0.67	0.02	0.01

Second, HHW grants have been awarded in California since 1990, a long time before the start of our study period in 2004. The counties didn't start to receive grant funds the same year they were announced; also the counties that received the grants the earliest were mostly the metro counties, such as Los Angeles, San Francisco, Alameda, Orange, and Fresno counties. From 1990 to 2003, some counties were also awarded funding more often than the others, such as Los Angeles, San Bernardino, San Diego, Santa Clara, and Ventura. Because of variation in the frequency and timing of grant disbursement, an extended analysis based on the sequence of the grants awarded to counties is useful to identify their heterogeneous effects over the years. This is not provided yet in this dissertation chapter, though.

Third, the HHW collection density variable aggregates the HHW of varied material categories. Some counties may have more uneven distribution in different material categories. For example, the *analysis of variance* (ANOVA) tests of the distribution of electronic waste show that the average amount of this waste was significantly higher in the north, compared to south and central. So if we break the analysis down by the material categories, the estimated effects of HHW grants may differ across these material categories. This analysis will be also done in the extended analysis later.

The spatial panel model addresses spatial autocorrelation issues in our data. However, the model estimations use a pre-determined weight matrix based on the nature of the spatial influences or the geography of the spatial units. Existing theories of spatial dependence typically do not derive a functional form for calculating the spatial weights (Plümper and Neumayer, 2010). Similarly, in pro-environmental contagion research, no theory guides the calculation of the weight matrix. So, to check the robustness of the results, we did sensitivity analysis using alternative weight matrices with an adaptive bi-square distance function, and fewer or more fixed neighbors.

A sensitivity analysis of estimations results using spatial weights with 25 and 35 nearest neighbors is provided in the Table Appendix C1[19]. These results show that when the number of neighbors was fewer than 30, the grants were estimated to have fewer effects on the HHW collected amount, but the HHW collection activities from close-by counties seemed to have greater effects on the HHW collection output in a county. This was the opposite when the number of neighbors was larger than 30.

One may suspect that HHW grants awarded in a county may affect the likelihood of awarding the grant in other nearby counties. To measure the spatial correlation of HHW grants, we calculated global Moran's *I* for each year and found no significant statistical evidence of any spatial patterns.

3.7. Discussion and Policy Implications

This article highlights the importance of considering location in assessing the effects of environmental related policies. The spatial patterns found in the results presented in earlier work by Lim-Wavde et al. (2017b) indicated the presence of spatial spillover mechanisms among close-by counties, in which could happen due to cooperation among the households or local governments in the counties. The cooperation occurs when households and local governments demonstrate good pro-environmental behavior. This is supported by our empirical analysis results as well.

The estimation results indicate a strong presence of pro-environmental spillovers that had a positive influence on HHW collection output. Ignoring them may

[19] *Neighbors* means the nearest neighboring counties within some distance; they are not necessarily adjacent to the county. The number of neighbors is used to calculate the adaptive distance-based weights.

overestimate the effects of HHW grants or other policies. So these effects should be taken into account when planning HHW-related policies in maximizing the household participation in HHW collection and recycling programs.

The findings also indicate positive effects of the HHW grants on the amount of HHW collected. We used a spatial random effects model with an IV to explore the causal relationships between the grants with HHW collection output. This model also can be used to estimate counterfactual impact assessments and to project future HHW collection output driven by HHW grants. This would be useful for policy-makers to estimate the amount of HHW collected and diverted from polluting the environment by allocating the grants effectively for getting the most households' participation.

3.8. Conclusion

This study had analyzed the spatial patterns of HHW collection density and then modeled the causal relationships between HHW grants and HHW collection density while considering the spatial spillovers from the neighboring counties. The model was developed to help policy-makers in assessing the effectiveness of their policies and programs through observational data by addressing confounding factors and plausible rival interpretation. This makes it so that policy-makers are more likely to uncover hidden biases in their policy and program evaluations, and to make better decisions about grant allocation for establishing and expanding HHW collection and recycling facilities.

This study used aggregated HHW collection data so we could not consider the variability in the HHW categories. In addition, the spatial spillovers would only happen when the people in the studied region cooperate to improve the quality of the environment (i.e., having good pro-environmental behavior). The spillover effects from close-by counties may not happen without adequate environmental awareness in the community. So the model used in this research is applicable to other regions when the people or the local government are keen to cooperate in maintaining good environmental quality for the whole region, such as in California, but it may not be applicable other regions or countries without such trait.

Besides spatial spillovers that come from cooperations between households and local governments, three kinds of spatial spillovers have been studied in the literature as a source of externalities: knowledge, industry, and growth spillovers (Capello, 2007). These spatially-bounded spillovers create value for other households and local governments without any corresponding expenses so they may complement the spatial spillovers of pro-environmental activities.

Knowledge or information, for example, about pro-environmental practice and environmental quality, can spread around across administrative boundaries so this kind of spillovers may also support the spatial effects of pro-environmental activities in close-by areas. Industry spillovers may involve a productive waste management firm or agency in the area that produces an increase in productivity to related firms thanks to technological advances and an increase in expertise. The concept of growth spillovers is generally linked to economic growth, but it can also be applied to the improvement of environmental behavior (i.e., the increase of pro-environmental behavior thanks to the growing pro-environmental behavior in the close-by regions). Future studies may consider these kinds of spillovers when the data to measure them is available.

Chapter 4. Assessing the Carbon Pollution Standards: Electric Power and Water Impacts

4.1. Introduction

To reduce greenhouse gas emissions for climate change mitigation, it is necessary to transition over time to a low-carbon electricity generation future. This may pose complex water challenges, as thermoelectric power plants are highly dependent on water, mainly for cooling purposes. Increasing droughts in some regions, such as in Texas in 2011 and California until mid-2016 (USDM, 2017), have exacerbated the water crisis. In 2010, the electric power industry made about 45% of total water withdrawals in the United States (Maupin et al., 2014). Without sufficient water supply, thermal generators will have to be shut down or curtail their operations (McCall et al., 2016). Thus, water should be an essential component of planning low-carbon electric power generation, especially in countries, states or regions with limited water resources (Zhai and Rubin, 2010).

Low-carbon energy options include fossil fuels with carbon capture and storage (CCS), renewables (wind and solar), and nuclear energy. Numerous studies have been conducted to explore the water impacts of low-carbon electric power generation at the plant, regional, and national levels (Zhai and Rubin, 2015). A shift to low-carbon electricity generation will either increase or decrease water use, depending on the choice of electricity generation systems and cooling technologies (Macknick et al., 2012a). The addition of an amine-based CCS system for 90% CO_2 capture at a pulverized coal power plant using wet cooling towers nearly doubles water consumption (Zhai et al., 2011). Using the regional energy deployment system (ReEDS) model to evaluate potential water use changes in the U.S. electric power sector, Macknick et al. (2012b) found that by 2030, the retirement of once-through cooling facilities will decrease national water withdrawals by 27% to 70% compared with 2010 withdrawal, whereas high penetration of coal-fired plants with CCS and nuclear plants will increase national water consumption by about 22% by 2050 compared with the 2010 level. In contrast, Tidwell et al. (2013) found that national water withdrawals may increase by roughly 1% or decrease by up to 60% relative to 2009 levels, while the change in national water consumption will range from -28% to +21%, depending on the implementation of CCS retrofit and a CO_2 emission price. However, Webster et al. (2013) found that a deep reduction requirement for CO_2 emissions will increase regional water withdrawals for electricity generation in the Electric Reliability Council of Texas (ERCOT) region because of additional water withdrawals for nuclear generation. Also, simultaneous constraints in both CO_2 emissions and water withdrawals will result in a different grid mix with a higher power plant fleet cost of electricity generation, compared to a single constraint on them (Qin et al., 2015; Macknick et al., 2012b).

Carbon pollution regulations will aid in limiting CO_2 emissions and facilitating the transition to low-carbon electricity generation. In 2015, the U.S. Environmental Protection Agency (EPA) established the New Source Performance Standards (NSPS) for limiting CO_2 emissions from new fossil fuel-fired electric generating units (EGUs) (U.S. EPA, 2015b). Under Section 111(d) of the Clean Air Act, the U.S. EPA also issued the Clean Power Plan (CPP). It establishes standards of performance for CO_2 emissions from existing EGUs, which are intended to cut sector CO_2 emissions by 32% by 2030 from their 2005 levels (U.S. EPA, 2015c). CO_2 emission reductions can be achieved by the three suggested building blocks: (1) improving the heat rate of existing coal-fired power plants; (2) increasing electricity generation from existing natural gas plants; and (3) increasing electricity generation from new renewable energy sources (EPA, 2015b). Although retrofitting the entire existing fleet of power plants with CCS technology is not possible, it may be feasible for some coal-fired EGUs, especially those that are fully or substantially amortized, fairly efficient, and have air pollution control systems and net capacities of more than 300 MW (Zhai et al., 2015; Talati et al., 2016).

Planning low-carbon electricity generation pathways for industry transition in a cost-effective, carbon regulation-compliant, and sustainable manner is important for both existing and new power plants. The overall policy-related goal of this study is to explore and evaluate the feasible transition pathways for power capacity expansion: with those that target compliance with regulations on the low-carbon pathways or the non-compliant pathways. Each pathway represents a scenario describing a possible expansion of the power system in the future based on specific assumptions on the technology choice, compliance with carbon pollution regulation, and water availability. The *business-as-usual* (BAU) *scenario* is the pathway that continues without trying to implement the carbon pollution regulations in a meaningful way. The *low-carbon scenarios* are the pathways that can comply with carbon pollution regulations by retrofitting CCS to existing plants or increasing generation from natural gas and renewables or a portfolio of low-carbon technologies. The overarching research question in this study is: how does each of the pathways affect water use for electricity generation? We also ask: What are the water impacts of complying with the carbon regulations? If retrofitting CCS to existing plants is considered, how will it affect the electricity generation and the water impacts? Additionally, how will water availability affect electricity generation under the carbon constraint and the choice of low-carbon generation technologies? To answer these questions, this study examines their impacts on water resources by developing a capacity expansion model to determine the optimal mix of low-carbon electricity generation technologies in the future and to support the electric power industry's efforts with the improvement of water management practices. This approach is also applied to explore how limits on water withdrawals affect the power grid mix and choices of water cooling technologies under the various scenarios.

In Texas, the electric power sector accounted for about 36% of the total state water withdrawal in 2005 (Kenny et al., 2009). This state experienced severe droughts in past years (USDM, 2017), which has increasingly limited the availability of water resources for the electric power and other sectors. ERCOT in Texas manages a power grid for 90% of the state's total electricity supply (ERCOT, 2015a, 2016),[20] and hence, is the region chosen for this case study-based future scenario analysis.

Section 2 presents an overview of the state and federal carbon regulations for existing and new power plants in the U.S. Section 3 offers a high-level statement of the integrated energy-and-water research framework for this research, followed by a discussion of the kinds of technology metrics that are relevant for power generation, energy and sustainability in the State of Texas as a case study context, as well as the data acquired from state and federal-level sources for this research. Section 4 then presents the power generation capacity expansion model, an overview of the power plant fleet transition pathways that are analyzed, and the key assumptions for running the model to obtain meaningful solution outcomes. Section 5 presents the modeling results, and Section 6 conducts additional sensitivity analysis to further

[20] The rest of the electricity load in Texas comes from other entities: Western Electricity Coordinating Council, Southwest Power Pool, and Southeastern Electric Reliability Council (Public Utility Commission of Texas, 2013). These are excluded here because the ERCOT grid is managed separately from them.

understand what can be learned from the results. Section 7 offers a discussion and interpretation of the main findings for the energy policy and power plant fleet transition context, and Section 8 concludes with contributions, limitations, and recommendations.

4.2. Carbon Regulations on Existing and New Power Plants

The final NSPS limits CO_2 emissions to 1,400 lb CO_2/MWh-g for new coal-fired EGUs and 1,000 lb CO_2/MWh-g for new natural gas-fired EGUs or 1,030 lb CO_2/MWh-g for base load natural gas-fired EGUs (U.S. EPA, 2015c). To meet the emission limit, new supercritical pulverized coal-fired (SC PC) power plants have to reduce emissions by 20%, requiring deployment of CCS for partial CO_2 capture (Ou et al., 2016). However, there is no need for CO_2 emission reductions at new natural gas-fired combined cycle (NGCC) power plants, which have a CO_2 emission rate less than the standards.

The targeted 2030 CPP-established uniform national emission performance standards for two categories of existing fossil fuel-fired EGUs: 1,305 lb CO_2 per MWh for steam units and 771 lb CO_2/MWh for stationary combustion turbines (CT). The final set of rules also presented state-specific *rate-based goals* and equivalent *mass-based goals*, reflecting each state's power generation mix in 2012. Given that a state has the flexibility to choose the emission compliance plan and emission mitigation measures, this study focuses on the mass-based compliance plan.

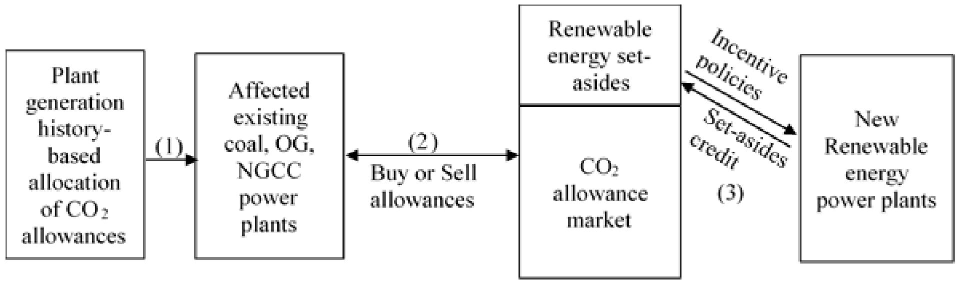
For a mass-based compliance plan, each state must implement a cap for CO_2 emissions allowed that are distributed across the existing affected EGUs. The affected sources include coal, steam from oil and gas, and natural gas (combined cycle) that were in operation or had commenced construction as of January 8, 2014, and they should meet the following criteria: serve a generator capable of selling greater than 25 MW to a utility power distribution system; and have a base load rating of greater than 260 GJ per hour (U.S. EPA, 2015c). In the mass-based plan without a CO_2 emissions cap for new sources, the state should address the potential generation leakage to new fossil fuel-fired sources.

To mitigate the risk of leakage, the U.S. EPA proposed set-aside allowances, such as a Clean Energy Incentive Program (CEIP) for rewarding early emission reduction projects (U.S. EPA, 2016), output-based set-asides that will incentivize existing NGCCs to increase their utilization (U.S. EPA, 2015d), and renewable set-asides to mitigate the leakage of CO_2 emissions to new NGCCs (U.S. EPA, 2015e). Assuming a national average allowance price of $13 per short ton, the EPA estimated that 5% of the total allowance represents a reasonable renewable set-aside level to mitigate the impacts of the transition (U.S. EPA, 2015e). This study takes into account renewable set-asides and output-based set-asides. With their implementation, the total allowance for the existing EGUs is the mass-based target minus the set-asides. In the EPA's proposed CPP federal plan, the total allowance is assigned proportionately to each unit's share of state-level historical generation that was calculated using its average annual net generation over the period from 2010 to 2012 (U.S. EPA, 2015d). The EPA also proposed an *allowance trading program* between the affected existing EGUs and renewable units within the state or with other states (U.S. EPA, 2015f). But, a recent study (Van Atten, 2016) showed that the EPA's proposed approach for allocating allowances in a program for existing plants may have a minor impact on emissions leakage to new fossil-fired power plants outside the program. Due to possible leakage, this study evaluates the mass-based approach that limits new-source emissions.

The EPA also estimated new source emissions associated with meeting increased electricity demand from 2012 (U.S. EPA, 2015g). The incremental generation needed was calculated using the projected load growth from 2012 minus the estimated generation from facilities under construction and generation growth in the affected EGUs and incremental renewable energy. Using the NSPS emission rate for NGCCs (1,030 lbs/MWh), the incremental generation needed to satisfy new electricity demand was converted to new source emissions. ERCOT's mass-based emission target is 157 million short tons. This is calculated by summing the allocated CO_2 allowances of ERCOT's existing EGUs proposed by the EPA (U.S. EPA, 2015d) plus the estimated set-aside allowances. Detailed allocations of emission allowances for the affected existing EGUs aggregated by electricity generation sources and cooling systems are in Appendix Table A1. Using the EPA's approach (U.S. EPA, 2015g), new source complements will be about 4.7 million short tons for the ERCOT region.

For set-asides, the approach outlined in the EPA's mass-based federal plan (U.S. EPA, 2015d) was adopted. Existing NGCCs with an average capacity factor of more than 50% are eligible to receive an allowance from set-asides. As the EPA assumed that the set-aside would incentivize the affected NGCCs to increase their generation to 60% of capacity, their *output-based set-aside* is calculated as follows: Baseline existing NGCC capacity $\times$ 10% $\times$ 8,760 hours $\times$ 1,030 lb/MWh-net $\times$ 1/2,000 (U.S. EPA, 2015d). Using this formula, the output-based set-aside for existing NGCCs in the ERCOT region is estimated at 15.8 million short tons. The optimal allocation of this set-aside to existing NGCC plants will be determined by the generation capacity expansion model presented later. The renewable set-aside for the ERCOT region is assumed to be 5% of total CO_2 allowances or about 7.8 million short tons. The allowance and set-aside trading mechanism is demonstrated in Figure 4.1. Existing coal, oil and gas, and NGCCs can buy CO_2 allowances from the renewable set-aside pool. This is an incentive for more renewable capacity. [21]

Figure 4.1. CO_2 Allowance Trading Scheme



Notes. (1) The CO_2 allowances are distributed to affected existing coal, OG, and NGCC power plants based on the unit level share of annual average generation from 2010 to 2012. (2) When an affected existing unit retires, its allocated allowances are transferred to renewable set-asides. (3) The allowances in renewable set-sides incentivize electricity generation via credits.

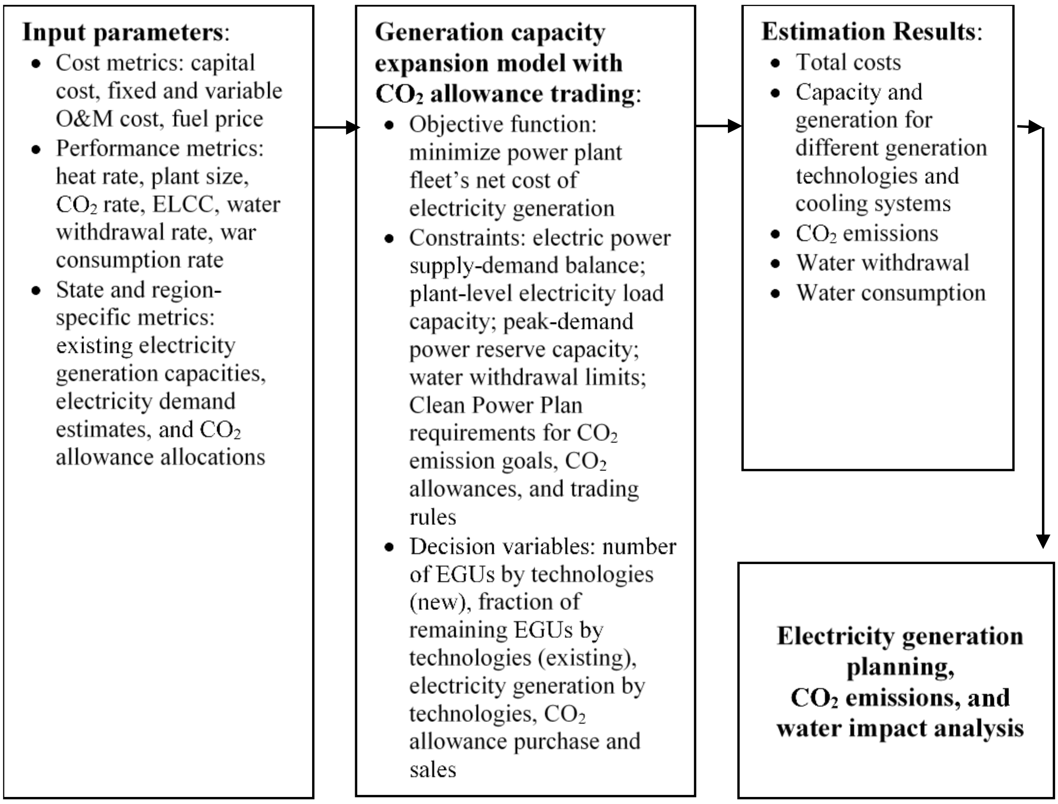
4.3. Assessment Framework and Data Sources

4.3.1. Framework and Problem Orientation

Figure 4.2 illustrates the energy-water modeling framework for electricity generation planning and assessing water impacts in scenarios with or without implementation of the carbon pollution standards. Although this research applies this framework to assess the implementation of the regulations in ERCOT, it is also applicable for other states in the U.S. and other countries. The parameters are customizable according to estimated electricity demand, fuel prices, and existing EGUs related to the targeted geographic scope for the analysis.

[21] The EPA proposed that a retired EGU can allocate renewable set-aside pool allowances if it did not operate for two calendar years (U.S. EPA, 2015e). However, in our model, we assume that the retired plants can keep the allowances for some time so that they can be bought by the existing plants that remain in the fleet as this seems to be a more realistic approach. If more coal plants retire, the electricity generation from existing NGCC plants will increase. In addition, if an EGU has an excess CO_2 allowance, it also can be sold in the CO_2 allowance market.

Figure 4.2. An Integrated Energy-Water Planning and Assessment Framework



With the goal of minimizing the fleet's net cost of electricity generation, this research uses an electricity capacity expansion model as a basis for optimizing investments in capacity with low-carbon energy technologies and determining the optimal grid mix of electricity generation, capacity retirement, and CO_2 allowance purchases and sales. The optimization is subject to a number of constraints for the fleet of plants, as described in Figure 4.2. The electricity generation technologies considered include conventional fossil fuel-fired power plants (e.g., coal, oil and gas, and natural gas), coal and natural gas-fired power plants with CCS, and nuclear and renewable energy power plants. The cooling technologies considered include once-through, recirculating, dry, and hybrid cooling. The candidate systems considered for new capacity expansion are the following: SC PC, SC PC with CCS, integrated gasification combined cycle (IGCC), NGCC, NGCC with CCS, gas CT, nuclear, wind, and solar photovoltaic (PV) technologies. EPA's regulations on cooling water intake structures, Section 316(b) of the Clean Water Act, state that no new capacity will employ once-through cooling.

4.3.2. Data Sources, Collection and Measures: Technologies and Metrics

We obtained performance and cost information on electric power generation and cooling systems from the U.S. Energy Information Administration (EIA) and the National Energy Technology Laboratory (NETL), plus results from power plant modeling.[22] Appendix Tables B1 to B3 summarize these metrics. For new PC, IGCC, and NGCC power plants with and without CCS for 90% CO_2 capture that use wet recirculating systems, estimates of heat rate, CO_2 emission, and water withdrawal rates, as well as capital, fixed and variable O&M costs were adopted from NETL's (2013) baseline report. Since this report uses costs in 2007 dollars, the costs were converted into 2012 dollars using the Chemical Engineering Plant Cost Index (CEPCI). For nuclear, gas combustion turbine, wind, solar, and hydropower systems, EIA's (2013) capital and operating cost estimates are used. For nuclear power, the heat rate reported by Webster et al. (2013) is employed. All cost assumptions and results are in 2012 dollars unless stated otherwise.

The *effective load carrying capacity* (ELCC) percentage is used to account for the amount of effective electricity generation capacity that can be counted on during peak periods (Garver, 1966). Similar to Webster et al. (2013), ELCC is assumed to be 100% minus the *effective forced outage rate* (EFOR) for thermoelectric units (nuclear, coal, gas combustion turbines, and hydro). It is set at 100% for NGCC plants because the EFOR can be offset by duct-firing capabilities that enable higher-

[22] These are used to determine the cost and performance metrics of the power plant technologies including new plants (23 types), existing plants (14 types), and existing PC and NGCC plants with CCS retrofits (1 and 3 types, respectively).

than-rated output generation during peak periods (Chase and Kehoe, 2000). For hydropower, it is assumed to be 93.4% due to the EFOR of 6.6% (EIA, 2014), however, the annual load of hydropower may be lower depending on water resource availability. The ELCC factor for wind power in Texas averages 24% for the coastal and west regions (ECCO International, 2013). The ELCC factor may decrease as solar penetration in the grid increases, it is assumed to be 53% for solar PV when the penetration rate is 10% (Perez et al., 2006). It is the same regardless of the cooling system type.

For a given power plant, the choices of cooling technology and CCS system also have some effects on the overall plant capital and O&M costs because of the differences in the CCS and cooling system capital cost and parasitic load between different cooling technologies (Zhai and Rubin, 2010, 2016). To account for the effects of CO_2 capture efficiency and cooling technology on EGU cost and performance, the Integrated Environmental Control Model (IECM v9.1) is employed to derive various correction factors used to adjust the base plant water use, heat rate, and costs.[23]

IECM was applied to model new PC plants: an SC PC plant without CCS, a plant with CCS partial capture of CO_2 according to the relevant CO_2 emission standards, and plant with CCS for 90% CO_2 capture using recirculating, hybrid, and dry cooling systems. Compliance with the CO_2 emission standard of 1,400 lb per MWh gross involves about 20% CO_2 capture at new SC PC plants. For plants with hybrid cooling, the cost and performance correction factors were estimated based on a comparative study by Zhai and Rubin (2016). The modeling results for these plants

[23] IECM (2015) is a power plant modeling tool developed by researchers at Carnegie Mellon University to provide estimates of the performance, water use, emissions, and costs for fossil-fuel fired power plants with and without CCS.

are provided in Appendix Table C1. By using these results for a PC plant with re-circulating cooling without CCS as the benchmark, the next derivation was for correction factors for the capital and O&M costs, and the heat and water use rates of the new PC plants with partial CCS with recirculating, hybrid, or dry cooling, and with or without CCS with hybrid or dry cooling.

Similarly, IECM is used to assess the performance and costs for new NGCC plants, including those without CCS and that implement CCS with recirculating, hybrid, or dry cooling. Appendix Table C2 provides the IECM modeling results for new NGCC plants and correction factors for capital, O&M costs, and heat rates for new NGCC with and without CCS using hybrid and dry cooling.

IECM was also used to estimate the performance and costs for existing PC and NGCC plants, including CCS retrofits. The plant specification and modeling results are provided in Appendix Tables C3 and C4. When CCS is retrofitted to existing plants, a retrofit factor of 1.25 for the CCS capital costs was applied to account for additional costs from difficulties in access to various plant areas and in integrating the CCS system into the plant (NETL, 2013; Zhai et al., 2015).[24]

The water withdrawal and consumption rates of nuclear, PC, and NGCC plants with once-through and recirculating cooling, and NGCC plants with dry cooling are based on the average water use factors from Macknick et al. (2012a). For other

[24] The IECM results show that, for a fully-amortized subcritical PC plant and an NGCC plant (GE 7FA) with recirculating cooling, the retrofit cost for full CCS is $1,409 per kW and 696 per kW, respectively. Due to the additional parasitic load of the CCS system, the plant net capacity of an existing coal plant with CCS retrofit decreases from 550 MW to 468 MW. Similarly, the net capacity of an NGCC plant with a CCS retrofit decreases from 400 MW to 344 MW. These results were then used to derive the correction factor for the capital, fixed and variable O&M costs, and the heat rate of existing PC and NGCC plants with once-through cooling, and for existing PC or NGCC plants with CCS retrofits with recirculating cooling, and existing NGCC plants with CCS retrofits with hybrid or dry cooling.

generation technologies, the rate was estimated using the correction factor calculated using water withdrawal rates in Webster et al. (2013) as the benchmark. Appendix Table D1 summarizes the factors for the costs, heat rates, and water use rates.

4.3.3. Data Sources, Collection and Measures: State-Level

A technical support document from the U.S. EPA (2015g) provides information on plant-level existing fleet capacity in the ERCOT region of Texas in 2012 (U.S. EPA, 2015h). After finding the cooling systems of these EGUs in the U.S. Geological Survey report on thermoelectric plant water use (Diehl and Harris, 2014), the capacity and historical generation of these EGUs were aggregated by electricity generation technologies and cooling systems, as shown in Table 4.1.

Table 4.1. Existing Generator Capacity and Electricity Generation, ERCOT in 2012

TECHNOLOGY/ COOLING SYSTEM	CAPACITY (GW)	GENERATION (MM MWh)
Coal/Once-Through	12.3	68.0
Coal/Wet-Recirc	8.7	42.2
OG Steam/Once-Through	13.4	7.1
OG Steam/Wet-Recirc	2.7	0.9
NGCC/Once-Through	3.0	11.0
NGCC/Wet-Recirc	29.4	107.4
NGCC/Hybrid	1.0	1.9
NGCC/Dry	1.7	4.9
Wind	11.2	29.4
Solar Photovoltaic	0.1	0.1
Nuclear/Once-Through	2.4	19.9
Nuclear/Wet-Recirc	2.7	18.5
Gas CT	5.5	5.8
Hydropower	0.6	0.5
Total Capacity	**94.5**	**317.7**

Notes. Sources: (1) Capacity and generation of EGUs in ERCOT for affected fossil-fuel-fired, existing gas CT, renewable EGUs (U.S. EPA, 2015h); the generation of unaffected fossil fuel-fired EGUs was about 9.3% of ERCOT's total electricity generation (U.S. EPA, 2015h). (2) USGS plant water use for EGU cooling, 2010 data (Diehl and Harris, 2014); (3) some cooling technology info available from the Internet, EIA Electricity Data Browser and 2013 EIA-923 database.

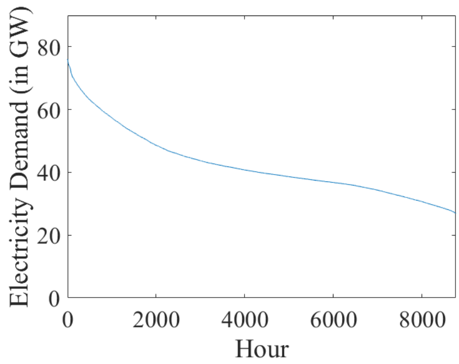
Overall, 42% of the ERCOT's existing fleet capacity uses recirculating cooling, 7.8% uses hybrid cooling, and 2.5% uses dry cooling, whereas 29% of the fleet capacity uses once-through cooling. The average plant heat rate for existing plants is 11.2 MMBtu per MWh for coal-fired EGUs, 12.2 MMBtu per MWh for OG steam plants, and 7.8 MMBtu per MWh for NGCC plants. (See Appendix Table B2 for a summary of their costs, CO_2 emissions, and water withdrawal rates.)

Fuel prices are estimated based on EIA's projections.[25] A recent load loss study (ECCO International, 2013) further reported that ERCOT's target reserve margin is 16.1%, which was adopted for the planned power reserve margin. The electricity demand projection was made based on historical loads. This research used ERCOT's electricity 8,760-hour demand data to build a load duration curve with peak demand of 65 GW in 2012 (ERCOT, 2015b). The load was adjusted to 90.7% of the total ERCOT 2012 load to exclude the historical generation of ERCOT's unaffected fossil fuel-fired EGUs considered in the model. A scale factor of 1.174 was then applied uniformly to develop the predicted load duration curve that represents the demand load in 2030. [26] (See Figure 4.3.)

[25] The average natural gas price for ERCOT plants was $3.00 per MMBtu in 2012 (U.S. EIA, 2012) and is projected to be $4.93 per MMBtu in 2030 in terms of the U.S. national annual fuel price growth rate of 2.8% (U.S. EIA, 2015a). The average coal price for ERCOT plants was $2.14 per MMBtu in 2012 (U.S. EIA, 2015b) and is expected to be $2.47 per MMBtu in 2030 for an annual growth rate of 0.8% (U.S. EIA, 2015a). The price of nuclear fuel was $0.29 per MMBtu in 2012 and is assumed to be $1.01 per MMBtu in 2030 (U.S. EIA, 2013a).

[26] The scale factor was estimated in terms of the expected 17.4% increase in Texas' net electricity generation from 2012, assuming 0.8% annual growth (U.S. EPA, 2015g; U.S. EIA, 2015b).

Figure 4.3. Predicted Load Duration Curve for ERCOT Electricity Demand in 2030



Notes. The load duration curve was scaled up by 1.174 from the load duration curve in 2012 (ERCOT 2015) that was adjusted to 90.7% of total load to exclude the historical generation of ERCOT's unaffected fossil fuel-fired plants.

4.4. Modeling Electricity Generation Capacity Expansion

4.4.1. Optimization Model for Energy Planning

A static generation capacity expansion model developed by Webster et al. (2013) was extended and applied by including CO_2 emissions allowance trading, renewable and output-based set-aside allowances, and consideration of EOR and CCS retrofits. The enhanced model recognizes new and existing EGUs subject to the corresponding CO_2 emission standards, includes CO_2 emission allowance and set-aside trading, and allows a retirement mechanism for existing EGUs. (The detailed optimization model is provided in Appendix E.) The objective function is to minimize the net costs of the power generation fleet that takes into account the total fleet costs minus the total offsets. The total fleet costs include capital investment, fixed and variable operating costs, fuel costs, CO_2 transport and storage costs (for EGUs with CCS), and CO_2 emission allowance costs. The total offsets include cash flows for selling the CO_2 captured by CCS for enhanced oil recovery (EOR); and excess CO_2 and renewable set-aside allowances.

This model uses mixed integer linear programming with simplified operations performing economic dispatch for an 8,760-hour load duration curve (Webster et al., 2013). Each generation technology is assumed to have the same capacity size in the model. The decision variables include the number of new EGUs for each generation technology and the amount of electricity generation for each of the demand blocks in the load duration curve.[27] In addition, a decision variable is needed to determine the remaining fraction of existing EGUs if any of the existing EGUs are retired. The model also includes decision variables for the amount of CO_2 allowances bought and sold in allowance trading associated with the CPP's mass-based compliance plan. It has five kinds of constraints in each period of operation for the fleet: (1) electricity demand and supply balance; (2) load capacity for minimum and maximum load of electricity generation; (3) reserve electricity generation capacity; (4) a water withdrawal limit as applicable; (5) and Clean Power Plan compliance for CO_2 emission allowances and EPA emission trading rules.[28]

4.4.2. Simulation Scenarios

To report on the effects of carbon emissions and water use limits on the future power grid, Table 4.2 summarizes the scenarios for comparison, including the *business-as-usual scenario* (BAU) without any carbon policy and water use constraints, and three *regulated low-carbon scenarios*.

[27] A smooth form of the *load duration curve* represents a one-year period of electricity demand, with 8,760 hourly load observations in descending order to populate a cumulative distribution function. Then, to support numerical simulation and enhance computational performance in this research, the duration load curve of load-ordered observations was *discretized*, so a year was composed of 438 *load strips* (Sherlali et al., 1982) of 20 hours each (with 438 load strips · 20 hours = 365 days · 24 hours = 8,760 hours, the number of hours in one year.) The *average hourly demand load* in each strip was used, as in other power system planning research (e.g., Roh et al., 2009; Baringo and Conejo, 2011). The exception is the left-most load strip in the curve – the *peak strip*, which contains the highest load observations; for this, *hourly peak demand load* was used.

[28] The integer programming and simulation model was created in MatLab R2015a (MathWorks, 2015). The mathematical details of the model are available in Appendix E.

Table 4.2. Summary of Future Scenario Regulations for Power Plant Operations

SCENARIO	NSPS, CPP, MASS-BASED, NEW SOURCE COMPLEMENTS TARGET	WITH CCS RETROFIT?	WITH WATER WITHDRAWAL LIMITS?
BAU	No	No	No
CPS	Yes	No	No
CPS + R	Yes	Yes	No
CPS + RW	Yes	Yes	Yes

The *BAU scenario* serves as a base case that meets electricity generation demand; it does not take into account any of the policy constraints on CO_2 emissions and water withdrawal. The *Carbon Pollution Standards* (CPS) scenario simulates the implementation of the CPP to achieve the CO_2 emission mass-based goal for existing plants in 2030. CO_2 emissions from new coal-fired plants are used to meet NSPS via amine-based CCS deployment for partial CO_2 capture. It adopts building blocks identified by CPP. It takes into account the CO_2 emission limit for affected existing and new EGUs. In addition to the mitigation measures identified, the *CPS + R scenario* also considers retrofitting amine-based CCS for 90% CO_2 capture on existing coal and natural gas-fired plants.

Because limits on water availability may affect the choice of low-carbon technologies in meeting the CO_2 emission limits, the *CPS + RW scenario* includes an additional constraint on water withdrawals. The drought in Texas in 2011 decreased state-wide reservoir water storage by about 30% from October 2010 to the minimum in November 2011, which was approximately 23.2 cubic kilometers (Scanlon et al., 2013), for example. For events like this severe drought, the CPS + RW scenario limits water withdrawal for low-carbon electricity generation to 50% of Texas' annual freshwater withdrawal. This was 3,833 billion gallons in 2010 (Maupin et al., 2014).

4.5. Results: Power Generation Pathway Scenarios and Water Impacts

4.5.1. Modeling Assumptions for Scenario Analysis

As discussed earlier, Table 4.1 summarizes the existing power capacity and electricity generation in 2012; Figure 4.1 presents the projected load duration curve in 2030; Appendix A summarizes the CO_2 allowance allocations for affected EGUs; and Appendix B summarizes the technical and economic metrics of new and existing power generation and cooling systems. The other major assumptions made for projecting the electricity generation fleet in 2030 are summarized in Table 4.3.

Table 4.3. Modeling Parameters and Assumptions for ERCOT in 2030

PARAMETERS	VALUES	PARAMETERS	VALUES
Coal price	\$2.47/MMBtu	CO_2 transport cost	\$3/short ton
Natural gas price	\$4.93/MMBtu	CO_2 storage cost	\$7/short ton
Nuclear fuel price	\$1.01/MMBtu	Economic book life time	20 yrs for wind; 30 yrs for others
Cumulative load growth (post-2012)	17.4%	Renewable set-aside	7.8 MM short tons CO_2
CO_2 allowance price	\$13/short ton	Renewable set-aside incentive	\$2.72/MWh
CO_2 mass-based goal	157 MM short tons	Set-aside allocation, wind/solar	54%, 46%
CO_2 new source goal	4.7 MM short tons	Output-based set-aside	15.8 MM short tons CO_2
CO_2 emission limit for new PC	1,400 lbs CO_2/MWh-g	Reserve margin	16.1%
CO_2 emission limit for new NGCC	1,000 lbs CO_2/MWh-g	Weighted avg. cost of capital	7.0%

Notes. (1) Fuel prices estimated from EIA's fuel databases and projections; (2) demand growth, CO_2 allowance price, mass-based goal, new source complement, renewable set-aside and incentive, and output-based set-aside estimated from EPA's approach in the CPP TSD (U.S. EPA, 2015d,e,g,h); (3) set-aside allocation ratios for wind and solar based on ratio of wind and solar electricity generation in 2030 estimated by EPA using Integrated Planning Model (IPM) v5.15; (4) CO_2 transport and storage costs based on Zhai et al. (2015) (5) reserve margin based on ERCOT's report (ECCO International, 2013); and (6) *weighted average cost of capital* (WACC) is a funds discount rate used in regulatory assessments.

4.5.2. Scenario Results and Analyses

Next presented are electricity capacity and generation estimates under the different pathway scenarios. Table 4.4 compares electricity capacity and generation mix by fuel for the scenarios. Although electricity generation in 2012 is estimated using the model with average fuel cost assumptions (U.S. EIA, 2012; U.S. EIA, 2013a), the generation mix results are close to the historical ones: 12.1% nuclear, 34.7% coal, 41.2% natural gas, 2.5% OG, 9.2% wind, 0.0% solar, and 0.2% water (U.S. EPA, 2015h). For the scenario analysis in 2030, about 2 GW of existing capacity from coal-fired EGUs with once-through cooling were excluded to reflect the scheduled retirement of multiple coal-fired Monticello EGUs in Texas in January 2018 (Power Engineering, 2017).

Table 4.4. Estimated Electricity Capacity and Generation Mix by Fuel Type, 2030

Fuel Type	Capacity Mix (%)					Generation Mix (%)				
	2012	BAU	CPS	CPS+R	CPS+RW	2012	BAU	CPS	CPS+R	CPS+RW
Nuclear	5.4	5.5	5.1	5.1	5.1	13.0	11.1	11.1	11.1	11.1
Coal	22.1	20.3	10.2	10.2	11.0	31.2	44.4	22.0	22.0	21.8
Gas	42.9	44.3	45.5	45.5	44.7	45.7	35.6	46.8	46.8	47.4
OG	17.0	17.2	15.9	15.9	15.9	0.0	0.4	0.7	0.7	0.3
Wind	11.9	12.0	18.8	18.8	18.8	9.9	8.4	14.3	14.3	14.3
Solar	0.1	0.1	3.8	3.8	3.8	0.0	0.0	5.0	5.0	5.0
Hydro	0.6	0.6	0.6	0.6	0.6	0.2	0.1	0.1	0.1	0.1

Notes. Electricity generation, CO_2 emission, and water use in 2012 were estimated using the model with fuel cost in 2012 dollars, as follows: $2.14/MMBtu for coal; $3.00/MMBtu for natural gas, $3.06/MMBtu for OG, and $0.288/MMBtu for nuclear power (U.S. EIA, 2012; U.S. EIA, 2013a).

Table 4.5 compares total cost, capacity, electricity generation, CO_2 emissions, water withdrawal, and water consumption. The total cost of the 2012 scenario only includes O&M and fuel costs. Appendix Table F1 provides the shares of electricity generation by power plant type when different cooling technologies are implemented. Estimates in this section pertain only to ERCOT.

Table 4.5. Comparisons of Cost, Capacity, Generation, CO_2 Emissions and Water Use

MODEL RESULTS	2012	2030			
		BAU	CPS	CPS + R	CPS + RW
Total cost ($ billions)	9.4	13.7	15.7	15.7	15.8
Total capacity (GW)	94	93	101	101	101
Total power generated (MM MWh)	296	348	348	348	348
CO_2 emissions (MM short tons)	167	231	161	161	161
new fossil-fueled plants	-	4	5	5	5
existing plants	-	227	157	157	157
Water withdrawal (billion gals)	2,877	3,766	3,532	3,532	1,917
coal	1,600	2,473	2,160	2,160	912
natural gas	372	345	379	379	82
OG	0	44	88	88	17
nuclear	903	903	903	903	903
Water consumption (billion gals)	81	102	67	67	91
coal	31	55	10	10	31
natural gas	30	27	36	36	39
OG	0	0	1	1	1
nuclear	18	18	18	18	18

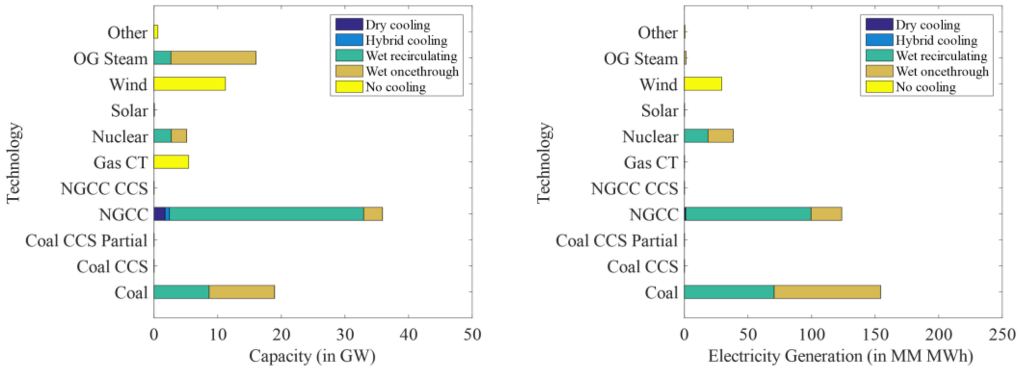
Notes. Electricity generation, CO_2 emissions, and water use in 2012 estimated using these fuel-related cost assumptions: $2.14/MMBtu for coal; $3.00/MMBtu for natural gas; and $0.28/MMBtu for nuclear power (U.S. EIA, 2012; U.S. EIA, 2013a). Water withdrawal for hydroelectric power of ~2 billion gallons for all scenarios excluded.

Overall, the total CO_2 emissions from the regional power sector would increase by 38% in 2030 under the BAU scenario without any carbon regulations and incentives for renewables, compared to 2012, while the total water withdrawal would increase by 31%. The future capacity and electricity generation from coal in the BAU scenario is higher than in 2012 due to the cheaper electricity generation cost of coal compared to natural gas. The low-carbon pathways will have similar total water consumption in 2030 relative to 2012 (about 0% to 0.3%). However, their total CO_2 emissions and water withdrawals will be lowered below the 2012 levels. In comparison between the low-carbon scenarios, electricity generation from coal in the CPS + R scenario is 3% higher than in the CPS scenario because of the CCS retrofitting on the existing coal EGUs. Due to the carbon pollution regulations, the capacity and electricity generation from natural gas, wind, and solar in the low-carbon scenarios are higher than in the BAU scenario. The electricity generation from EGUs with once-through cooling, especially existing coal-fired units, dominates the total water withdrawal from the power sector. It is highest in the BAU scenario at 41% and lowest in the CPS + RW scenario at 21%. Water consumption is also highest in the BAU scenario and lowest in the CPS scenario which has a smaller amount of water consumption from coal-fired EGUs than NGCC plants.

Under the BAU scenario in 2030, 1.1 GW of new NGCC plants are required to meet increased generation demand. (See Figure 4.4 and Table 4.4.) In addition, no existing plants need to be retired. Consequently, the capacity factor of PC plants increases to 93%. The fleet electricity generation is estimated to be 44% from coal and 36% from natural gas.

Figure 4.4. Projections for the Business-As-Usual Scenario, 2030

(a) Electricity Capacity (GW) **(b) Electricity Generation (MM MWh)**

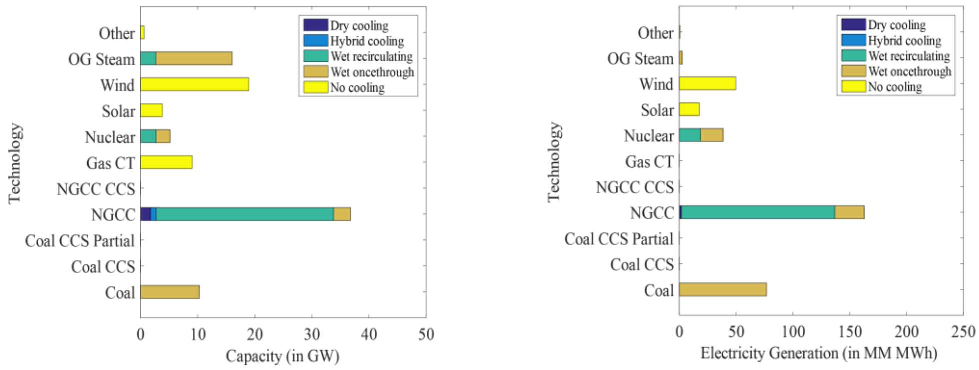


The CPS and CPS + R scenarios have the same results. The results show that 1.7 GW of new capacity from NGCC plants will be needed to meet regional electricity demand while adhering to the emission cap. (See Figure 4.5.) About 8.7 GW of existing coal EGUs are estimated to retire. Compared to the BAU scenario, the generation from coal is 50% lower, but the generation from natural gas is about 32% higher. The renewable set-asides provide economic incentives to increase capacity from new renewable EGUs to about 13 GW. Also, the resulting generation shares increase to 14% and 5% with a mix of wind and solar sources, respectively.

The generation share of EGUs with recirculating cooling will be 63%, higher than in the BAU scenario at 59%.

Figure 4.5. Projections of Electricity Capacity and Generation under the CPS Scenario

(a) Electricity Capacity (GW) **(b) Electricity Generation (MM MWh)**



With the water withdrawal limit set to 50% of Texas' 2010 level (1,900 billion gallons), the CPS + RW scenario results indicate that the generation from existing coal and NGCC plants with once-through cooling will decrease by ~45 MM MWh and ~23 MM MWh, respectively. 4.7 GW of coal EGUs with once-through cooling and 3.1 GW of coal EGUs with recirculating cooling would retire instead of 8.7 GW of coal EGUs with recirculating cooling as in the CPS and CPS + R scenario (See Figure 4.7.)

In the scenarios without a limit on water withdrawal, generation from thermoelectric plants is estimated at 33% to 41% for plants with once-through cooling, and 59% to 63% for recirculating cooling, with small shares for hybrid and dry cooling. The scenario that limits water withdrawal is estimated to have lower electricity generation (~21%) from plants with once-through cooling, and more generation (~74%) from plants with recirculating cooling. Electricity generation from plants with hybrid and dry cooling will increase slightly but still remain very low.

Figure 4.6. Projections of Electricity Capacity and Generation under the CPS + R Scenario

(a) Electricity Capacity (GW) **(b) Electricity Generation (MM MWh)**

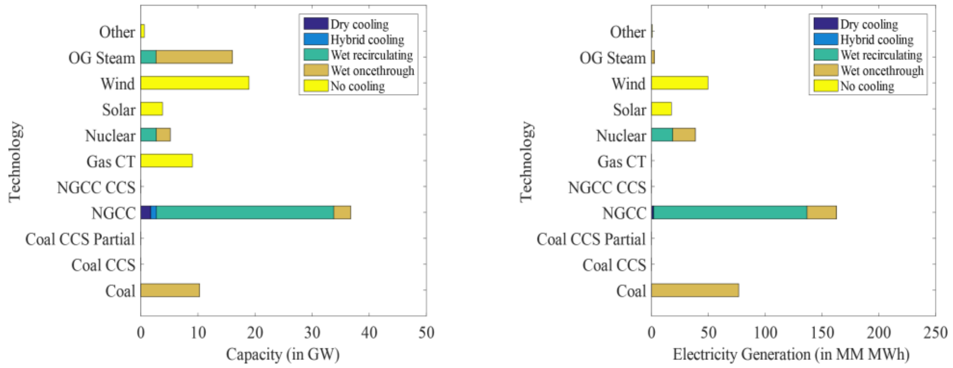
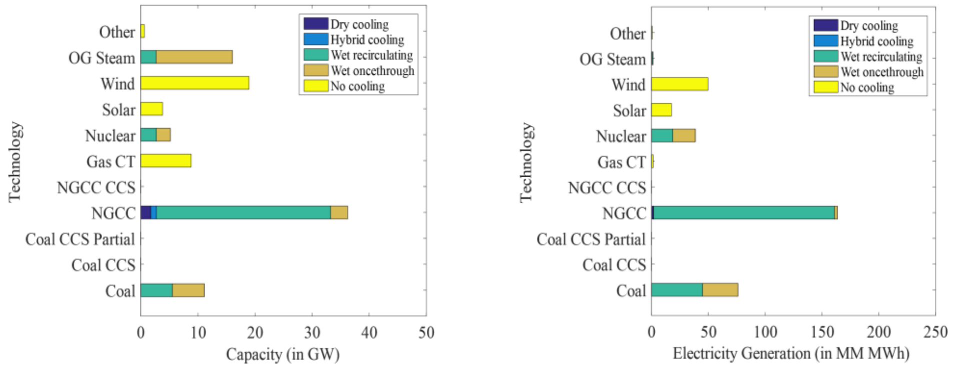


Figure 4.7. Projections of Electricity Capacity and Generation under the CPS + RW

(a) Electricity Capacity (GW) **(b) Electricity Generation (MM MWh)**



4.6. Sensitivity Analysis

To understand future pathways for environmentally-conscious power production for the ERCOT region in 2030, one must understand how CO_2 emissions regulations and relevant key factors impact water withdrawals and consumption, and affect the fundamental aspects of regional sustainability at the expected levels of electricity demand. Sensitivity analysis is conducted to evaluate changes in the power plant generation capacity model's outputs as a single parameter input is varied. The analysis is performed on those parameters that affect the power generation mix, which consequently affects the water impacts. The sensitivity analysis results are then compared with the nominal case estimates presented in the scenario results in Section 5.2. These support some of the key energy sustainability policy analytics aspects of this research.

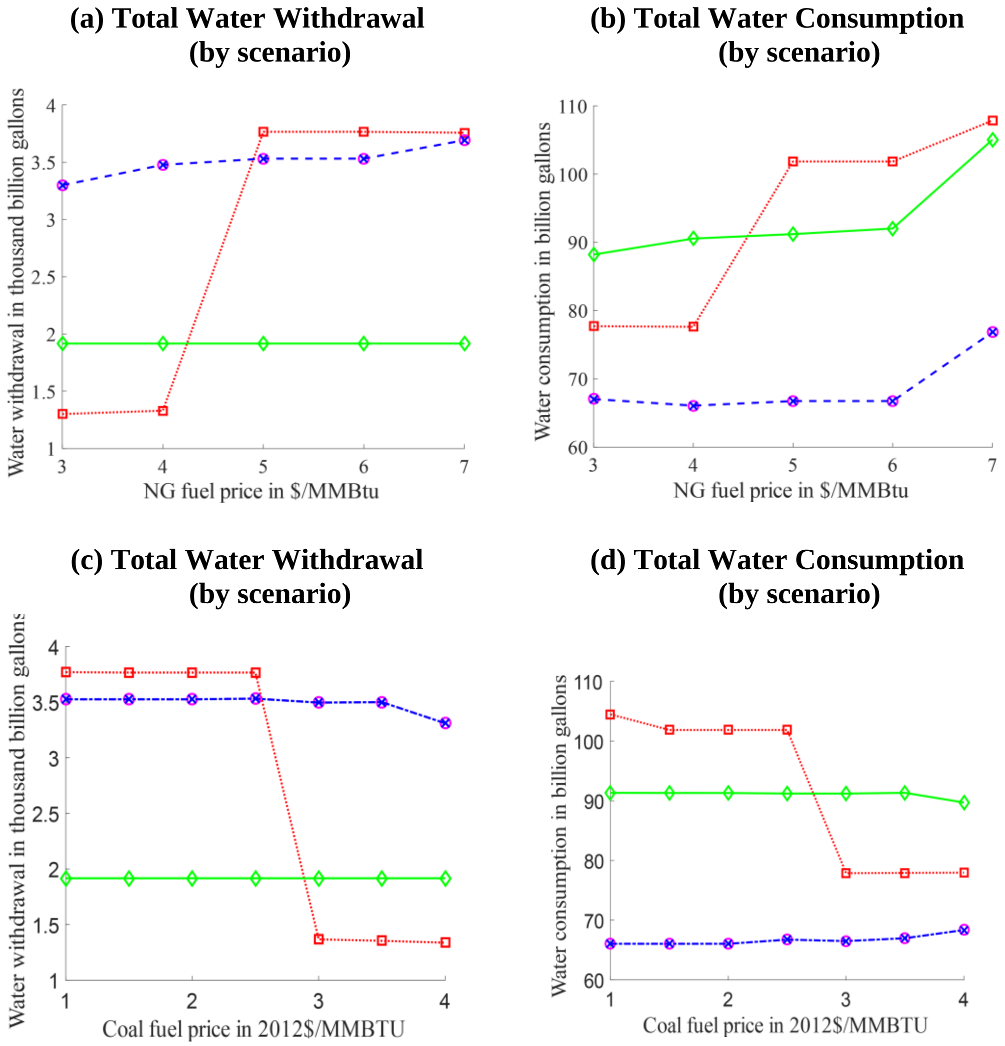
4.6.1. Price Sensitivity

Price projections for 2030 vary and affect the generation mix estimates in different ways. Next discussed is the sensitivity of prices that will influence the water impact estimates under all scenarios.

Natural Gas and Coal Prices The electricity generation mix is sensitive to coal and natural gas prices. The Henry Hub Natural Gas spot price is projected to have an annual market growth from 0.6% to 4.38% since 2012 (U.S. EIA, 2015a). After applying this growth rate to Texas' natural gas price in 2012, the natural gas price is estimated to range from \$3.34 per MMBtu to \$6.49 per MMBtu. Likewise, the coal price in 2030 is projected by EPA for the ERCOT region to range from \$2.1 to \$3.2 per MMBtu (in 2011 dollars) (U.S. EPA, 2015i). So, a sensitivity analysis was performed by covering the gas price from \$3 to \$7 per MMBtu and the coal price from \$1 to \$3 per MMBtu, respectively. See Figure 4.8 for the total water use by scenario.

Under the BAU scenario, generation from natural gas is estimated to increase by 124% with respect to the nominal case, and will substitute for all generation from coal when the natural gas price is at \$3 per MMBtu. Consequently, water withdrawal is estimated to be as low as 1,300 billion gallons. Electricity generation from coal would reach the nominal case level (123 MM MWh) when the natural gas price is \$5 per MMBtu or higher so withdrawal is estimated to be as high as 3,800 billion gallons. (See Figure 4.8a.) It is the opposite when the coal price is lower or higher than \$2.5 per MMBtu. (See Figure 4.8c.) Also, total water consumption is estimated to be 24% lower when the NG price is lower than \$4 per MMBtu, and the same as the nominal case when the NG price is higher than this price. The opposite trends are observed when the coal prices are higher and lower than \$2.5 per MMBtu.

Figure 4.8. Water Withdrawal and Consumption by Natural Gas and Coal Prices



Notes. This sensitivity analysis is for these scenarios: ···□··· BAU; --o-- CPS; ---x--- CPS + R; —◊— CPS + RW.

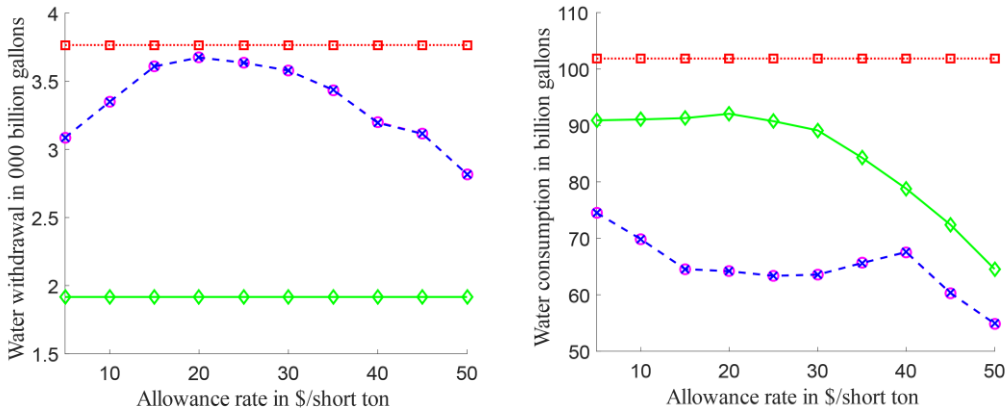
Under the CPS and CPS + R scenarios, when the NG price increases, generation from coal increases by 5% above the nominal case at the \$7 per MMBtu price level. There is also an increase of electricity generation from solar PV by 11% at the \$7 per MMBtu price level and nuclear by 24% at the \$7 per MMBtu price level due to high electricity generation cost at NGCC plants and the CO_2 emission constraints, respectively. The resulting water withdrawal is estimated to increase by 1.5% when the NG price is higher than \$5 per MMBtu. The water consumption may decrease by 1% when the generation from renewables becomes cheaper than from NGCC, but increase by 16% when the generation from nuclear power increases by 49%. In contrast, a low coal price does not increase the electricity generation from coal due to the CO_2 emissions constraints. A high coal price (at \$4 per MMBtu) results in a decrease in electricity generation from coal by 12% below the nominal case and an increase in electricity generation from NGCC by 5% above the nominal case.

Under the CPS + RW scenario, the water consumption estimates are generally higher than in the CPS + R scenario because of more electricity generation from EGUs with recirculating cooling than the ones with once-through cooling. The water consumption increases by 16% when the NG price is higher than \$6 per MMBtu, but it is similar to the nominal case even though the coal price is \$1 per MMBtu.

CO_2 Allowance Price. EPA recently estimated that for a 3.0% average discount rate, the *social cost of CO_2* would be \$50 per metric ton (2007 dollars) in 2030 (Interagency Working Group on Social Cost of Carbon, 2013). So a sensitivity analysis was performed for the allowance price ranging from \$5 to \$50 per short ton to examine how it would influence the electricity generation mix and water use.

As the allowance price increases, the electricity generation from renewable gradually increases and generation from new NGCC decreases to zero when the allowance price is higher than \$25 per short ton under the CPS and CPS + R scenarios. At \$25 per short ton, the generation from new renewable increases to about 72 MM MWh that is almost twice the generation in the nominal case (at \$13 per short ton) so retrofitting CCS to meet the demand under the CO_2 emission limit is not required. At \$40 per short ton, the water withdrawal is approximately 23% higher than the estimates in the nominal case because of more electricity generation from existing coal-fired EGUs with once-through cooling instead of new NGCC plants. However, this water withdrawal level is still much lower than the BAU scenario. Water consumption is also estimated to decrease by 15-19% to 55 billion gallons when the allowance price reaches $50 per short ton as the electricity generation from renewable energy increases by 136% to 171 MM MWh. Figure 4.9 provides total water withdrawal and consumption by scenario.

Figure 4.9. Water Withdrawal and Consumption by CO_2 Allowance Price



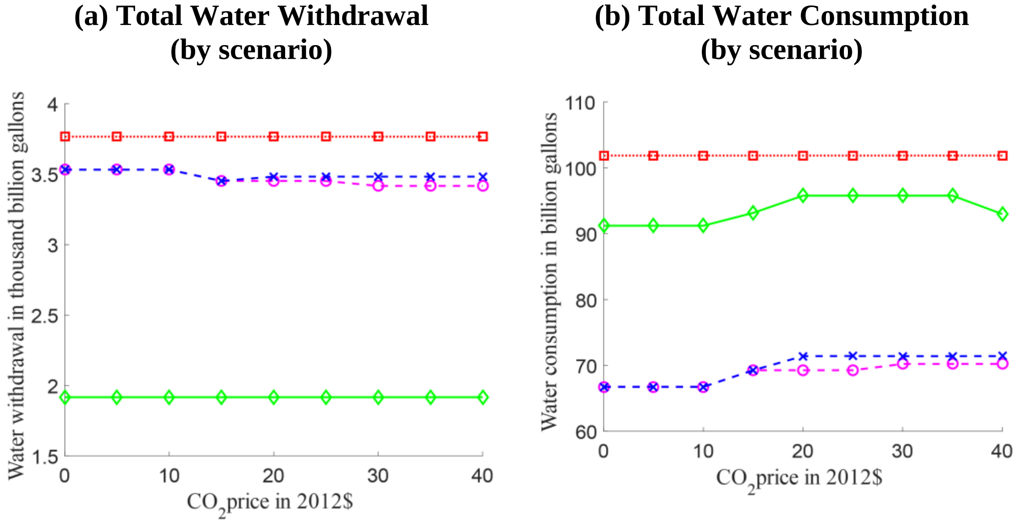
Notes. This sensitivity analysis is for these scenarios: ···□··· BAU; --o-- CPS; ---x--- CPS + R; –◊– CPS + RW.

CO_2 Sale Price for Enhanced Oil Recovery. Fossil fuel-fired plants with CCS systems can earn income from the sale of the captured CO_2 for use with EOR operations (IEA, 2015). A Sensitivity analysis is performed for CO_2 sale price up to $40 per short ton. A higher CO_2 sale price gives an incentive for power plants to employ *carbon capture, utilization, and storage* (CCUS) to diminish carbon pollution from fossil fuel-fired plants so more capacity and generation is yielded by coal-fired and NGCC plants with CCUS. Figure 4.10 provides total water withdrawal and consumption by scenario.

Under the CPS scenario, when the CO_2 sale price is lower than $15 per short ton, the electricity generation mix stays the same as in the nominal case, so no changes are observed in water withdrawals. When the CO_2 sale price is $15 per short ton or higher, electricity generation from new coal-fired EGUs with 20% CCS increases. This is because the generation cost of coal-fired units with CCUS becomes competitive with the cost of new NGCC generation. At $40 per short ton, the total water withdrawal is only 3% above the nominal case level, but the total water consumption is increasing by 5% due to an increase in new coal EGUs with CCUS using recirculating cooling systems.

Under the CPS + R scenario, when the CO_2 sale price is $15 per short ton or higher, more than 90% of existing coals units with recirculating cooling (in terms of the capacity) are estimated to install the CCS retrofit. The electricity generation from these units reaches 2.7 MM MWh at the sale price of $40 per short ton. Retrofitting CCUS reduces CO_2 emissions so EGUs can sell their CO_2 allowances to other coal-fired EGUs. As the CO_2 sale price increases, the total water consumption is estimated to increase by 7% under this scenario because of an increase in the electricity generation from existing coal-fired EGUs with CCS using recirculating cooling systems.

Figure 4.10. Water Withdrawal and Consumption by CO_2-EOR Price



Notes. This sensitivity analysis is for these scenarios: ···□··· BAU; --o-- CPS; --x-- CPS + R; –◇– CPS + RW.

Even with the sale price of $40 per short ton of CO_2, the total water withdrawal is lower by ~6% under the CPS and CPS + R scenarios than under the BAU scenario. However, the total water consumption in the CPS + R and CPS + RW scenarios is about 30% higher than in the BAU scenario because of additional water consumption from the plants with CCS retrofits that use recirculating cooling systems.

4.6.2. Electricity Demand

For a given emissions target in 2030, the demand for electricity can affect the low-carbon energy roadmap and water use for electricity generation. Corporate and individual consumers may reduce their electricity demand by employing various energy efficiency measures and on-site renewable energy technologies. Conversely, electricity demand may be higher than expected due to high economic growth, widespread adoption of electric vehicles, and the large industrial loads of the future. ERCOT (2015c) also has estimated that there could be a 10% difference in their forecasts based on the historical volatility of the weather. This prompted additional sensitivity analysis on the demand with the scale factor varied from 1.0 to 1.5 of 2012 demand level.[29]

Figure 4.11 shows the total water withdrawal and consumption at different levels of electricity demand under all the scenarios. Under the BAU scenario, as electricity demand increases, generation from new NGCC EGUs with recirculating cooling increases gradually to 38% of fleet generation at the scale factor of 1.5. However, there is a decrease in generation from existing NGCCs with once-through

[29] A scale factor of 1 is about 15% lower than the nominal case level, and a scale factor of 1.5 is about 28% higher than the nominal case level. These cover a +/-10% difference from the nominal case level based on the historical volatility of the weather (ERCOT, 2015c). These also may cover the increase of demand for high forecasted economic growth of 1.5% annual growth in the West South Central Region (U.S. EIA, 2015a). This is about 1.3 times the 2012 demand level.

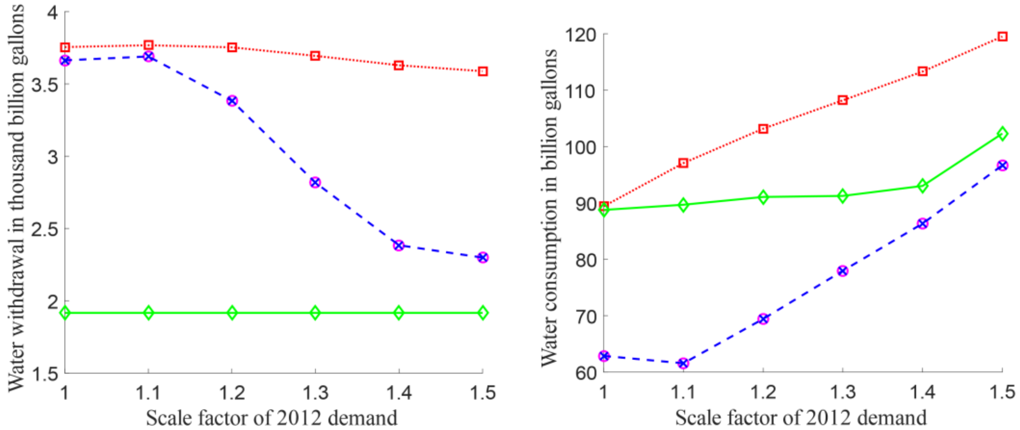
cooling (by 54% of nominal case level). As a result, the water withdrawal under the BAU scenario decreases slightly with the demand increase. In contrast, the low-carbon scenarios have much lower total water withdrawal (roughly 2,300 billion gallons) at different levels of electricity demand because of decreased electricity generation from existing coal-fired and NGCC EGUs with once-through cooling under the given emission constraint. On the other hand, the total water consumption increases as electricity demand increases in all the scenarios except for the CPS + RW scenario, which is illustrated later.

Under the CPS and CPS + R scenarios, the total water withdrawal is estimated to be about 4% higher than the nominal case at the scale factor of 1 (no increase in electricity demand from 2012 level) because the increase in generation from new renewable incentivized by set aside allows an increase in the electricity generation from existing coal with once-through cooling by 19% above the nominal case level. (See Figure 4.10a.) When the electricity demand in 2030 is 30% more than the 2012 level (corresponding to the scale factor of 1.3), more generation from NGCCs (by 37%) are required to comply with the given emission limit. When the scale factor is 1.5, the generation from nuclear will increase by 24%. This results in an increase by 4% in the water withdrawal and by 45% in the water consumption. (See Figure 4.11b.)

Under CPS + RW scenario, as demand increases, the water withdrawal stays under the water limit, but the water consumption increases gradually. This is because of an increase of generation from existing NGCC EGUs with recirculating cooling by 66% at the scale factor of 1.5.

Figure 4.11. Water Withdrawal and Consumption by Scale Factor of Demand in 2012

(a) Total Water Withdrawal (by scenario) **(b) Total Water Consumption (by scenario)**



Notes. This sensitivity analysis is for water withdrawal and consumption under these scenarios: ···□··· BAU; --o-- CPS; ---x--- CPS + R; –◊– CPS + RW.

4.7. Discussion

States have the authority to manage their electric power grids. In February 2016, the implementation of the CPP was halted due by the U.S. Supreme Court (2016), which granted a stay order until related legal issues were resolved. Then in early 2017, a presidential order put the carbon pollution standards proposed by the EPA, including NSPS and CPP, under review (The White House, 2017). Now it is still up to the individual states whether to implement these regulations for deeply reducing the CO_2 emissions from the electric power sector or to continue the status quo. The scenario analysis results show the consequences of the pathways that may be selected by a representative state.

If the regulations are not implemented, the state's electricity generation will depend on the fuel costs, particularly coal and natural gas prices in the market. For ERCOT in Texas, when the cost of generating electricity from coal is cheaper than from natural gas, generation from coal sources may reach 47% of its power fleet's generation mix. Consequently, the fleet's total CO_2 emissions will be 45% higher than in 2012 by 245 million short tons. So ERCOT should be prepared for a high increase in total water use for electricity production because it will have 31% higher water withdrawal, and 29% higher water consumption than in 2012.[30]

Otherwise, electricity generation from natural gas may reach 80% of the fleet's generation mix when the cost of generation from natural gas is very low. Hence, total CO_2 emissions will be 120 million short tons, or 29% lower than in 2012. This is lower than the CO_2 emission cap for ERCOT under CPP. So even with the status quo, ERCOT may achieve the CO_2 emission level recommended by the U.S. EPA, if the natural gas price is low (< \$4 per MMBtu), or if the coal price is very high (> \$3 per MMBtu). Additionally, total water use will be 58% (1,300 billion gallons of withdrawal) and 4.9% lower (78 billion gallons of consumption) than in 2012, respectively.

Over time, electricity generation from coal has been declining in the U.S. due to low natural gas prices in production from shale. If the trend of decreasing prices persists, U.S. power companies will retire more coal-fired plants in the coming years.[31] The announced retirement of 1.8 GW from the coal-fired Monticello Power Plant with once-through cooling shutdown by January 2018 is an example (Power Engineering, 2017). This retirement plan has been included in our analysis. Just a week after this announcement, the Big Brown and Sandow Coal Plants, with 2.4 GW nameplate capacity combined, were announced to be closed, but the closure is still under reliability review by the ERCOT at the time of the writing (Koenig and

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[30] Our scenario analysis for Texas has not considered the Texas' Regional Haze Plan that regulates the emissions of sulfur dioxide (SO_2) from coal plants.

[31] In 2017, the U.S. Secretary of Energy issued a Notice of Proposed Rulemaking (NOPR) directing the Federal Energy Regulatory Commission (FERC) to ensure that "certain reliability and resilience attributes of electric generation resources" (i.e., electricity generation from coal and nuclear as base load) are fully valued. FERC has no jurisdiction over ERCOT's grid though. So this ruling will not affect ERCOT's power system.

Sorg, 2017). If the ERCOT permits the closure, this will decrease the capacity from coal-fired plants with once-through cooling and recirculating cooling by 1.2 GW and 1.3 GW, respectively. This may further diminish overall CO_2 emissions and water use.

If ERCOT selects a scenario with carbon pollution regulation, such as NSPS and CPP, CO_2 emissions will be guaranteed to be lower. This is because the CO_2 allowance and CO_2 limit for the new EGUs have restricted the electricity generation from coal so ERCOT will need to add new NGCC and renewable EGUs to meet the load demand. In the scenario with CCS retrofits to existing EGUs, ERCOT will need to add fewer new NGCC EGUs. Water withdrawal will be around 2,800 to 3,400 billion gallons, which is much lower than in the status quo pathway of business-as-usual. The CO_2 allowance price determines electricity generation from renewable and natural gas sources; the higher the price, the more generation will come from renewable sources (and less from new NGCCs). Also the lower the fleet's total water consumption. Water withdrawal may still increase slightly as the CO_2 allowance price increases when generation from coal EGUs with once-through cooling increases.

In another carbon-regulated scenario, ERCOT may consider retrofitting CCS systems to existing coal-fired EGUs. The CO_2 sale price for EOR will matter. As generation from coal-fired EGUs with CCS retrofit increases, the higher the fleet's total water withdrawal and consumption will be. In both carbon-regulated pathways (with or without CCS retrofitting), electricity load demand plays an important role in total water withdrawal and consumption. When the increase in the demand is very low, water withdrawal may go as low as 2,800 billion gallons. In contrast, total water withdrawal may reach 4,000 billion gallons and consumption may reach 140 billion gallons when the CO_2 sale price is $40 per short ton.

In the scenario with limits due to drought, water withdrawal is fixed, but the fleet has more generation from recirculating-cooled than once-through cooled EGUs. The change in water withdrawal is affected by generation changes from plants with once-through cooling systems. When the fleet has more generation from renewable and NGCC power plants with recirculating cooling, the generation from plants with once-through cooling may decrease, which results in lower water withdrawal but this will slightly increase total water consumption, which is consistent with Macknick et al. (2015).

For all of the scenarios, adding new plants with once-through cooling is not considered because of regulations on cooling water intake structures under Section 316(b) of the Clean Water Act. As such, the total water withdrawal of all low-carbon scenarios in 2030 will be similar to or less than the 2012 level, even with an increased demand for electricity.

Load demand determines the upper bound of water consumption in all scenarios, except in the scenario with water withdrawal limit, so energy-efficiency measures to lower load demand will be crucial to decrease the electric power sector's water use. Also, a high CO_2 allowance price will reduce the fleet's water consumption due to the high penetration of renewable energy.

4.8. Conclusion

The framework presented is for assessing water impacts in scenarios with or without carbon pollution standards. Its application was demonstrated for the implementation of the U.S. EPA's Clean Power Plan. The generation capacity expansion model includes CO_2 emissions allowance trading, renewable and output-based set-aside allowances, and consideration of EOR and CCS retrofits. However, some caveats accompany the analysis, especially for the scenarios with high penetration of renewables, which has not taken into account power transmission and distribution constraints or expansion and energy storage that secure the electric grid's stability and reliability.

This study contributes to the assessment of electricity generation pathways for compliance with carbon regulations and their water impacts in the future. The results for electricity generation and water impacts in ERCOT show that complying with NSPS and CPP will result in lower water use than in 2012 because of an increase in electricity generation from renewable sources and via NGCC plants.

The sensitivity analysis, however, shows that withdrawal may be approximately 20% higher when the CO_2 allowance price reaches $40 per short ton in the carbon regulation-compliant scenario because of more electricity generation from existing coal-fired EGUs with once-through cooling. Also, if retrofitting CCS to existing fossil-fuel-fired plants is considered, water withdrawal may be about 41% higher than the estimate when the CO_2 sale price for EOR is $15 per short ton or higher. Even so, this is still lower than in the status quo pathway when the cost of electricity generation from coal is lower than from natural gas. Finally, for these pathways, the occurrence of drought is likely to reduce electricity generation from EGUs with once-through cooling, and increase that from EGUs with recirculating cooling, but this will slightly increase total water consumption.

Under the Trump Administration, the EPA proposed to repeal the Clean Power Plan. Our findings still provide a hopeful view of future electricity generation that is environmentally sustainable in terms of CO_2 emissions and water impacts. Although the carbon pollution regulations of the Obama Presidency may not be implemented due to shifts in the political economy of the U.S., we nevertheless observe that strong underlying market forces are likely to cause the electric power sector to become more sustainable over time. Implementing elements of the Clean Power Plan regulations will lead to deeper reductions in CO_2 emissions though.

Although the findings and the policy implications discussed in this study were pertinent and specific the U.S. power fleet, the policy insights are applicable to electric generation planning in any other countries that consider using carbon regulations for transitioning to low-carbon electricity generation while meeting the rising energy and the water constraints. This study highlights the importance to assess the water requirement for thermal electricity generation in the long-term electricity generation planning to ensure environmental sustainability. This study shows that transitioning to more electricity generation from natural gas and renewable sources can reduce overall water use from the power sector. However, one must consider other issues in water and energy planning, such as the thermal plants' cooling systems, Carbon Capture and Storage systems, CO_2 allowance and sale price, and water resource availability.

Chapter 5. Policy Analytics Research Practice

Environmental sustainability is a complex problem that involves dynamic interactions between people and the environment. Experts and scientific researchers have an important role in studying these interactions and informing the relevant stakeholders: policy-makers and citizens.

My research lies in the interdisciplinary area of IT, sustainability and environmental management. The research journey started from reviewing prior research in IS and environmental sustainability for my qualifying exam. The literature provided a big picture about various contexts and methodologies from different disciplines used in addressing environmental sustainability issues. Furthermore, the increasing access to public data and big data, coupled with my training in data analytics, statistics, econometrics, math programming, and policy analysis, has opened up considerable opportunities to transform data into policy insights. These ultimately led my research towards policy analytics research.

Framing the research questions. Research begins with a general problem that can be narrowed down to a more specific research question. Identifying the environmental issues to address with policy analytics does not happen overnight. The problem identification and research questions articulated in Essay 1 were the results of many hours of discussions with Prof. Robert J. Kauffman, my research advisor at Singapore Management University (SMU), and Prof. Gregory S. Dawson from Arizona State University, who had worked closely with CalRecycle when he was a Senior Consultant at PwC. The inclusion of spatial dependency issues in Essay 2 was the result of collaboration with Prof. Tin Seong Kam from SMU. The water impacts of electricity generation issues and the research questions were the results of discussions and collaboration with Prof. Haibo Zhai and Prof. Edward S. Rubin from Carnegie Mellon University (CMU) during the Living Analytics Research Centre (LARC)'s exchange program with CMU in 2014 to 2015.

Understanding theories and contextual knowledge. Before looking at the data, it is crucial to understand relevant theories and the context of environmental issues.

In Essay 1, utility maximization theory was first used to explain how informedness, HHW programs, and demographic characteristics impact the amount of waste collected and recycled at the household level. To formulate the hypotheses and develop the econometric models, I also learned about HHW, its risks to the environment, and its collection and recycling programs in California. Although I have never lived in California, fortunately, the U.S. EPA and CalRecycle provided comprehensive documentation about HHW.

Understanding household behavior, and waste collection activity-related spillovers among the nearby counties in California is necessary to explain the spatial patterns and dependencies found in the exploratory analysis results in Essay 2. I considered diffusion of pro-environmental behavior and also collaboration among local governments to explain the spillover of HHW collection activities. I also learned from Prof. Gregory S. Dawson about cultural differences between Northern and Southern California that may explain the hotspots of HHW collection activities in the north. These theories and contextual knowledge allowed me to develop econometric models to establish causal relationships between the effects of HHW policies, such as HHW grants and the spillover effects, on HHW collection output.

As I started working on Essay 3, I learned about electric power engineering and approaches from the "Energy and the Environment" course at CMU and from my

CMU advisors. By understanding the context, I could develop the electricity generation capacity expansion model for the assessment framework. The contextual knowledge also allowed me to evaluate the model outputs and gain the policy insights.

Taking advantage of open data. The vast amount of open data provided by government agencies and non-government organizations potentially creates amazing opportunities to gain policy insights. Essay 1 used annual HHW data from California. Besides the waste data, CalRecycle's Data Central provides a lot more data on the waste materials, facilities, grant database, and demographic information. Essay 2 used the waste data and the location data from GADM, a database of the location of administrative areas or boundaries. Essay 3 used historical data and information related to electricity generation, costs, power plants performance and their environmental impacts from U.S. EPA, U.S. Energy Information Administration (EIA), National Energy Technology Laboratory (NETL) and previous studies on water impacts of electricity generation.

Overcoming data challenges. Nevertheless, using open data for analytics is not without any challenges. Missing data was one of the issues in the county-level data in California. For example, although there are 58 counties in California, the demographic data from the American Community Survey only contains the data of 40 counties. To include the demographic variables in the econometric model, I removed the counties with the incomplete demographic data.

Lack of control over the data quality is another issue with the waste data, which is also a common issue for any other secondary data. For this issue, I ran the Bonferroni outlier test to identify unusual data points that might be caused by measurement errors or unusual activities in particular year or county. For the consistency of the model estimates, these outlier data points were excluded from the empirical analysis. However, this approach is not applicable when we need a balanced panel data.

Future fuel price and load demand level in Essay 3 were estimated using historical level in 2012 and an annual growth rate based on the U.S. EIA's Annual Energy Outlook. However, future prices may be lower or higher than the ones forecasted due to various factors and uncertainties. Sensitivity analysis was performed to overcome this issue by varying each variable that matters to evaluate the changes in the electricity generation capacity expansion outputs.

Extracting policy implications. Policy implications were presented at the end of each essay. Writing policy implications are not just about presenting the research results and insights, they should fit the context of the results. Having a conversation or discussion with co-author or mentor who has policy knowledge helped me develop an understanding of where to begin. For Essays 1 and 2, before writing the policy implications, I discussed the model estimation results with my advisor and Prof. Gregory S. Dawson, who knew about California better than me. For Essay 3, I also discussed the carbon pollution regulations and U.S. power sector with my CMU advisors and his Ph.D. students, Shuchi Talati and Jeffrey Anderson, in the Department of Engineering and Public Policy.

Presenting research results at conferences. Before completing the research, I was fortunate to have opportunities to present the preliminary results of Essay 1 and Essay 2 in two conferences. The first one was at the International Conference on Informatics, Environment, Energy and Application 2016 in Hong Kong, China. The second one was at the iConference 2017 in Wuhan, China. The feedback and comments that I received during the presentation sessions were invaluable to the research. While attending the other researchers' presentation sessions, I also learned new ideas and methods used in other related fields.

Writing a research article for a leading environmental sustainability economics journal. Publishing a full research article in a peer-reviewed journal makes the research and findings in my work available to the scientific community and policy-makers. Essay 1 has been published in the *Resources, Conservation, and Recycling* journal, a multi-disciplinary journal in the areas of economics, environmental science, and waste management. Essay 2 is in preparation for submission to *Applied Geography* in that discipline, It publishes research with environmental sustainability content, as well as statistics, econometrics, data mining, cluster analysis, machine learning, and other computer science methods. And Essay 3 is in preparation for submission to *Energy Policy*, which focuses on a range of issues involving electricity, power, fuel, energy and related policy issues. While preparing these manuscripts for journal submission, I have learned so much from my advisors: how to pick a journal, how to write an excellent review response, how to interact with reviewers, editors, and publishers, and so forth. All the hard work pays off after getting the paper accepted for publication.

Expanding my research networks. Real-world problems are complex and often require multi-disciplinary expertise. Through the conferences and workshops that I attended, I was connected with experts and scientists from Computer Science, Information Science, Environmental Science, Economics, and Social Science. I have followed their research in ResearchGate, the Social Science Research Network, and elsewhere, and some of them have followed mine as well. The research networks will potentially pave the way for future impactful research collaborations.

Last, the research experience during my Ph.D. program has given me a better understanding of the policy analytics research for tackling environmental sustainability issues. With the help of cutting-edge technologies, advances in data analytics, and novel methodologies in machine learning, statistics, and econometrics, I aspire to contribute to the pursuit of environmental sustainability through impactful research as a multidisciplinary scientist.

Chapter 6. Conclusion

This dissertation has demonstrated the power of data analytics in uncovering policy insights in the form of impact assessment, elasticity analysis, and numerical simulation using publicly available data. The insights are valuable to policy-makers in evaluating current policies and circumstances, and making informed decisions for planning their next policies and strategies in the areas of waste, energy, and water management.

Essay 1 contributes policy insights from empirical research on household informedness that influences the collection and recycling of household hazardous waste (HHW). Household informedness in California included HHW-related public education and environmental quality information. The proposed model was able to identify and measure the effects of household informedness in increasing the HHW collection activities, and also in decreasing the generation of HHW at source. Both effects were good for the environment because the more HHW collected, recycled, neutralized, or reduced leads to less environmental contamination by the waste. The quantification of the effects resulted in an impact estimator, *household informedness elasticity of HHW collection and recycling output*. This offers a tool to gauge the responsiveness of HHW collected and recycled as the level of informedness increases through more provision of educational and environmental quality information.

Essay 2 also contributes policy insights in HHW management from the assessment of the impact of HHW grants and the spatial influence from the pro-environmental activities of nearby areas (i.e., spatial pro-environmental spillovers) on HHW collection outputs. The analysis of causal relationships enabled the unbiased measurement of the effects of grants and also the spatial effects from the nearby counties in California. This analysis is useful to gauge how much HHW grants generally influenced the amount of HHW collected considering the influences from nearby areas. In addition, the model developed in this research can be used to simulate possible outcomes with different decisions or possible outcomes in other states with different geographic and demographic environments, through counterfactual analysis

Essay 3 contributes insights to the energy, water, and carbon pollution issues of the future. The future scenario and sensitivity analysis results using an optimization model showed possible pathways in the future for Texas in meeting the electricity demand with or without carbon pollution regulation and water constraints. The results provide clearer picture to relevant policy-makers about the consequences in the future when making the decision to implement the carbon pollution regulation.

The essays are examples of policy research that are enabled by fusion analytics – which combines machine methods and explanatory empiricism. In an attempt to uncover causal relationships from observational data, I applied quasi-experiment design and employed advanced econometrics, such as a system of equations model, panel data, spatial assessment, and instrumental variable methods. I also employed environmental model and math programming to simulate future scenarios with parameters and assumptions about future electricity demand, market prices for power plant fuels, and environmental constraints.

There are some limitations in the research in this dissertation. As with any other quantitative empirical study, data limitations are an issue in Essays 1 and 2. As the data that directly represent informedness level were not available, we used proxies that are relatively close to what is the critical information content that is needed.

Essay 1 used the number of projects with HHW-related educational programs, however, the number may not reflect the different quality levels of the educational campaigns. Similarly, Essay 2 used the dollar value of the grants to support the projects to develop or expand HHW collection and recycling facilities. The dollar value of the grants may also depend on the different nature of the projects and the skill of the project manager. If more detailed data were available, the effects would be able to be estimated more accurately. I did my best to use modeling and identification strategies that isolated these unobservable effects though.

Uncertainty is another limitation in my dissertation, particularly in Essay 3. Although I conducted sensitivity analysis based on the possible variability in market price and electricity demand in the future, there is still considerable uncertainty in the future. Breakthroughs or new technology discoveries in energy research may decrease the estimated cost of certain energy sources, for example, via solar energy panel research, natural gas extraction, and so forth.

Furthermore, the complexity of the problems and systems involved may not be fully accounted for by the models that are used. However, I did my best to select the influential factors and relationships that represent the general understanding and issues that are essential for policy assessment and evaluation.

Future studies should include other contemporary analytics methods, such as data mining, text analytics, and deep learning to obtain more fine-grained data from various data sources to develop a holistic model for understanding the impacts of related policies on people and the environment. Besides more data, adaptive empirical research designs should also be implemented to take into account the possibility of unexpected changes in the future.

Environmental sustainability is everyone's responsibility, not just the government's, but also individual citizens and firms. Sustainability has increasingly become very important in a modern world with growing cases of environmental deterioration, pollution, and loss of diversity. The research potential of policy analytics for environmental sustainability is limitless. This dissertation is my first step as an aspiring environmental policy scientist to contribute relevant insights that address the disruptive relationship between human social systems and the environment.

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Appendices for Chapter 2

APPENDIX A. METRO AND NON-METRO COUNTIES IN CALIFORNIA

Table A1. County Definitions in the State

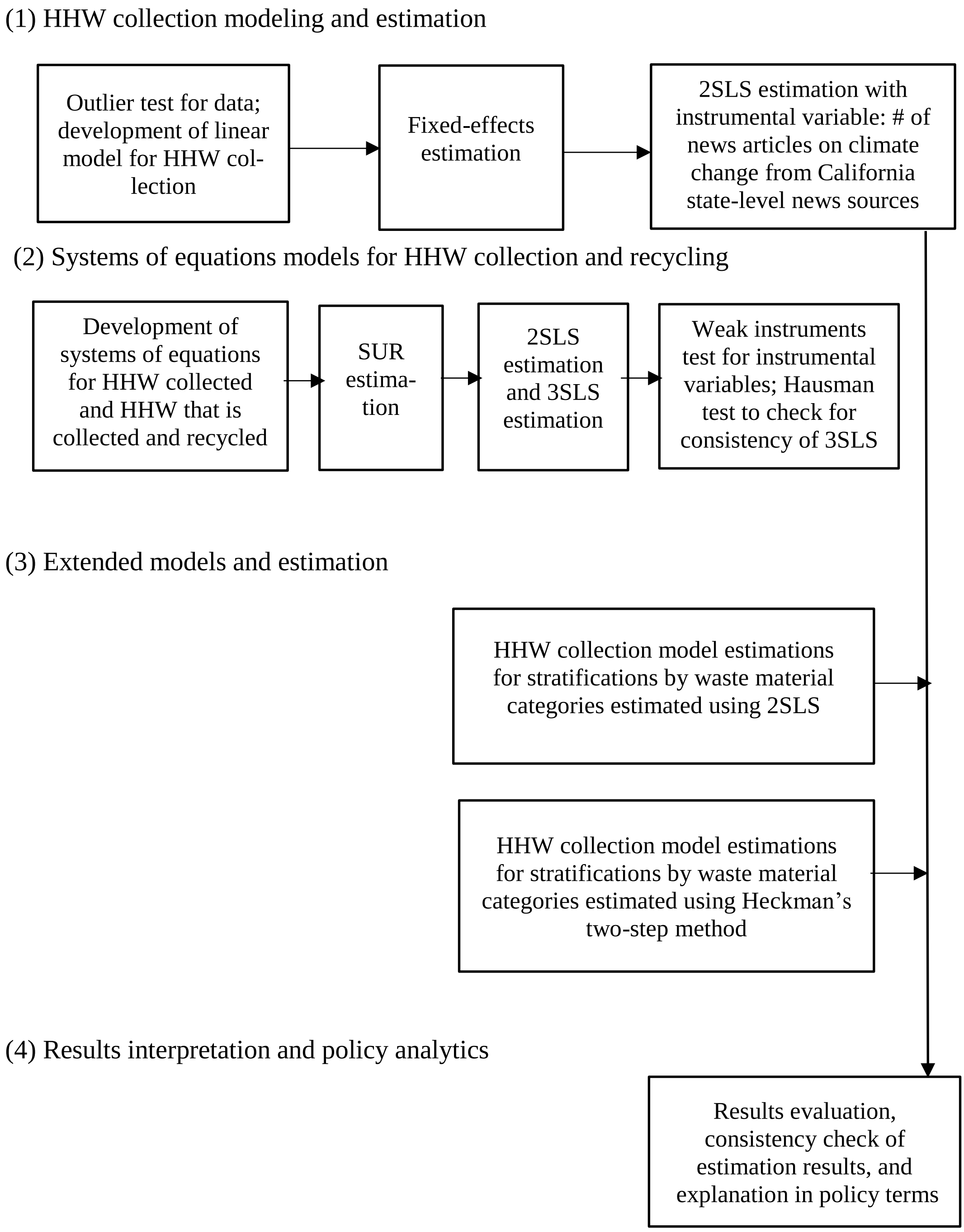
CODE	DESCRIPTION
Metro Counties	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Non-Metro Counties	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area
Source: U.S. Office of Management and Budget (2010)	

Table A2. CA Counties and Their Rural-Urban Continuum Codes (*RUCC*)

RUCC	COUNTY
1	Alameda, Contra Costa, El Dorado, Los Angeles, Marin, Orange, Placer, Riverside, Sacramento, San Benito, San Bernardino, San Diego, San Francisco, San Mateo, Santa Clara, Yolo
2	Fresno, Kern, Merced, Monterey, San Joaquin, San Luis Obispo, Santa Barbara, Santa Cruz, Solano, Sonoma, Stanislaus, Tulare, Ventura
3	Butte, Imperial, Kings, Madera, Napa, Shasta, Sutter, Yuba
4	Lake, Mendocino, Nevada, Tehama, Tuolumne
5	Humboldt
6	Amador, Calaveras, Colusa, Glenn, Modoc, Siskiyou
7	Del Norte, Inyo, Lassen, Mono, Plumas
8	Alpine, Mariposa, Sierra, Trinity
Source: U.S. Office of Management and Budget (2010)	

APPENDIX B. MODELING AND ESTIMATION

Figure B1. Empirical Research Process Used in This Study



APPENDIX C. ESTIMATION RESULTS: ADDITIONAL DETAILS

Table C1. SUR Estimation Results for HHW Collected Versus Collected and Recycled

VARIABLES	HHW COLLECTED Coef. (SE)		HHW COLLECTED AND RECYCLED Coef. (SE)	
Intercept	-4.67***	(1.63)	-10.88**	(4.54)
ln(*HHWRecQ*)	0.46***	(0.02)	—	
3YCum#PubEdu	0.02	(0.03)	0.11	(0.08)
#MCLViolLg	0.02*	(0.01)	0.04*	(0.02)
#MCLViol	-0.003***	(0.001)	-0.004**	(0.002)
DHHWGrant	0.08	(0.05)	0.00	(0.12)
ln(*Density*)	-0.05*	(0.03)	-0.11	(0.07)
EduHS%	1.80***	(0.37)	3.80***	(0.99)
ln(*MeanHHIncome*)	0.61***	(0.16)	1.17***	(0.40)
ln(*Pop*)	0.35***	(0.03)	0.65***	(0.09)
EWasteFee	—		0.01	(0.01)
UsedOilFee	—		0.84	(1.37)
$RUCC_2$	—		0.03	(0.17)
$RUCC_3$	—		0.12	(0.26)
$RUCC_4$	—		0.66*	(0.34)
$RUCC_5$	—		-0.93**	(0.42)
Adj. R^2	83.0%		43.4%	

Notes. Model: Simultaneous equations; estimation: SUR; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Estimated with the SystemFit package in R (Henningsen and Hamann, 2007). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table C2. 2SLS Estimation Results for HHW Collected Versus Collected and Recycled

VARIABLES	HHW COLLECTED COEF. (SE)		HHW COLLECTED AND RECYCLED COEF. (SE)	
Intercept	-4.20**	(1.66)	-10.77**	(4.73)
ln(*HHWRecQ*)	0.46***	(0.03)	—	
3YCum#PubEdu	-0.13*	(0.08)	0.51**	(0.25)
#MCLViolLg	0.02**	(0.01)	0.04	(0.03)
#MCLViol	-0.003***	(0.001)	-0.004*	(0.002)
DHHWGrant	0.15**	(0.06)	-0.20	(0.17)
ln(*Density*)	-0.05*	(0.03)	-0.12	(0.07)
EduHS%	1.69***	(0.39)	4.23***	(1.06)
ln(*MeanHHIncome*)	0.55***	(0.17)	1.23***	(0.42)
ln(*Pop*)	0.37***	(0.04)	0.56***	(0.11)
EWasteFee	—		0.00	(0.02)
UsedOilFee	—		1.63	(1.49)
$RUCC_2$	—		0.08	(0.18)
$RUCC_3$	—		-0.02	(0.29)
$RUCC_4$	—		0.55	(0.36)
$RUCC_5$	—		-1.20**	(0.47)
Adj. R^2	82.0%		38.7%	

Notes. Model: simultaneous equations; estimation: 2SLS; 333 obs. Dep. vars.: HHW collected is ln (*HHWCollQ*); HHW recycled is ln (*HHWRecQ*). Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Estimated with SystemFit package in R (Henningsen and Hamann, 2007). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

APPENDIX D. MATERIAL CATEGORIES ANALYSIS

Table D1. Fixed-Effects Model with 2SLS Estimation Results Stratified by Material Categories

MATERIALS	RECLAIM-ABLES	FLAMM. & POISON	ELECT. WASTE	ACIDS	BASES	OXIDIZER	ASBESTOS
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	-12.60*** (4.59)	-24.64*** (4.19)	-30.53 (22.52)	-30.65*** (4.36)	-40.69*** (7.70)	-33.93*** (6.27)	-75.60*** (16.65)
3YCum#PubEdu	-0.39* (0.20)	-0.19 (0.20)	2.05 (1.33)	-0.01 (0.21)	-0.16 (0.37)	0.20 (0.30)	-0.99 (0.79)
#MCLViolLg	0.00 (0.02)	0.03 (0.02)	0.16 (0.12)	-0.01 (0.02)	-0.02 (0.04)	0.07* (0.03)	0.05 (0.09)
#MCLViol	-0.004* (0.002)	-0.004** (0.002)	-0.010 (0.009)	0.000 (0.002)	0.004 (0.003)	-0.004* (0.002)	-0.018*** (0.007)
DHHW Grant	0.37** (0.15)	0.23* (0.14)	-0.65 (0.90)	0.16 (0.14)	0.23 (0.25)	0.11 (0.21)	0.80 (0.55)
ln(*Density*)	-0.07 (0.07)	-0.05 (0.06)	-1.56*** (0.34)	-0.10 (0.07)	0.04 (0.12)	0.00 (0.10)	-0.22 (0.25)
EduHS%	2.18** (1.03)	3.50*** (0.95)	14.46*** (5.12)	4.08*** (0.98)	2.05 (1.74)	2.68* (1.42)	3.25 (3.76)
ln(*MeanHH Income*)	1.35*** (0.40)	2.08*** (0.36)	1.38 (1.99)	2.18*** (0.38)	3.10*** (0.67)	2.55*** (0.55)	5.61*** (1.45)
ln(*Pop*)	0.72*** (0.10)	0.85*** (0.09)	1.77*** (0.53)	0.92*** (0.10)	0.97*** (0.17)	0.81*** (0.14)	1.28*** (0.37)
UsedOilFee	-1.45 (1.33)	—	—	—	—	—	—
EWasteFee	—	—	-0.02 (0.08)	—	—	—	—
$RUCC_2$	-0.26 (0.17)	0.14 (0.16)	-0.53 (0.85)	0.22 (0.16)	0.04 (0.29)	-0.20 (0.24)	-0.82 (0.63)
$RUCC_3$	-0.34 (0.27)	0.31 (0.25)	-0.90 (1.36)	0.24 (0.26)	-0.34 (0.46)	-0.33 (0.37)	0.73 (1.00)
$RUCC_4$	-0.22 (0.35)	0.44 (0.32)	-1.93 (1.70)	0.16 (0.33)	0.56 (0.58)	0.58 (0.47)	-2.19* (1.26)
$RUCC_5$	-0.38 (0.44)	1.09*** (0.41)	-9.91*** (2.24)	0.46 (0.43)	2.17*** (0.75)	1.24** (0.61)	-1.18 (1.63)
Adj. R^2	50.0%	60.3%	12.0%	62.3%	47.3%	50.7%	27.6%
Wu-Hausman	7.67***	1.32	2.05	0.05	0.75	0.43	1.54

Notes. Model: fixed-effects; dep. var.: natural log of HHW collected amount +1 (to retain data points with native values of 0) for each waste material category: Reclaimable (*ReclCollQ*), Flammable and Poison (*FPCollQ*), Electronic (*EWCollQ*), Acid (*AcidCollQ*), Asbestos (*AsbCollQ*), Base (*BaseCollQ*), Oxidizer (*OxCollQ*) Waste, 333 obs. PCB, Universal Waste omitted due to poor model fit. Base case $RUCC_1$ is omitted. Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*; weak instrument stat. = 46.24***. Coef. with $p < 0.10$ highlighted in gray; coef. with $p < 0.05$ are in bold and italics also. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table D2. Fixed-Effects Model with Heckman Estimation Results Stratified by Material Categories

MATERIALS	RECLAIMABLES	FLAMM. & POISON	ELECT. WASTE	ACIDS	BASES	OXIDIZER	ASBESTOS
VARIABLES	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	***-8.70**** (3.58)	***-20.87***** (3.27)	14.06 (41.26)	***-29.11***** (3.83)	***-34.34***** (6.89)	***-23.39***** (4.87)	-47.15 (39.55)
3YCum#PubEdu	***-0.33***** (0.06)	***-0.17***** (0.05)	0.08 (0.12)	***-0.16***** (0.05)	***-0.26***** (0.08)	***-0.29***** (0.06)	***-0.42**** (0.79)
#MCLViolLg	0.00 (0.02)	***0.04**** (0.02)	0.04 (0.03)	-0.01 (0.02)	-0.02 (0.02)	**0.03*** (0.02)	0.12 (0.12)
#MCLViol	***-0.003**** (0.001)	***-0.004***** (0.001)	-0.003 (0.002)	0.001 (0.001)	0.002* (0.001)	***-0.004***** (0.001)	-0.005 (0.012)
DHHW Grant	***0.30***** (0.09)	***0.18**** (0.08)	-0.03 (1.08)	0.15* (0.09)	-0.14 (0.19)	0.10 (0.12)	0.13 (0.54)
ln(*Density*)	-0.04 (0.05)	-0.02 (0.05)	***-0.31***** (0.11)	-0.07* (0.04)	-0.04 (0.08)	-0.03 (0.06)	-0.10 (0.17)
EduHS%	***2.56***** (0.82)	***3.78***** (0.73)	4.09 (2.91)	***3.30***** (0.70)	-0.41 (1.19)	-0.25 (0.84)	***-11.76**** (4.78)
ln(*MeanHH Income*)	***1.04***** (0.33)	***1.76***** (0.30)	-0.83 (3.47)	***2.09***** (0.35)	***2.83***** (0.57)	***1.82***** (0.41)	5.08 (3.11)
ln(*Pop*)	***0.67***** (0.07)	***0.80***** (0.06)	***0.55***** (0.12)	***0.92***** (0.06)	***0.94***** (0.10)	***0.87***** (0.08)	***0.62***** (0.23)
UsedOilFee	***-2.15**** (0.93)	—	—	—	—	—	—
EwasteFee	—	—	***0.07**** (0.03)	—	—	—	—
$RUCC_2$	***-0.30**** (0.13)	0.10 (0.11)	0.12 (0.22)	0.13 (0.11)	-0.13 (0.19)	-0.17 (0.15)	-0.74 (0.46)
$RUCC_3$	***-0.44**** (0.19)	0.21 (0.17)	-0.44 (0.34)	0.28 (0.17)	0.19 (0.28)	-0.30 (0.21)	0.97 (0.68)
$RUCC_4$	**0.39*** (0.23)	***1.02***** (0.20)	0.64 (0.40)	***1.06***** (0.22)	***1.20***** (0.36)	***1.20***** (0.27)	0.83 (1.67)
$RUCC_5$	***-0.39**** (0.19)	***1.11***** (0.04)	***-2.13***** (0.62)	0.46 (0.30)	***2.09***** (0.39)	***1.40**** (0.24)	0.48 (1.70)
Inverse Mills Ratio	-2.02 (2.32)	-2.07 (1.61)	-3.29 (12.91)	-0.11 (1.32)	-2.11 (1.65)	***-1.74**** (0.71)	-0.34 (2.90)
Adj. R^2	64.7%	73.6%	20.5%	76.0%	60.4%	65.6%	19.8%

Notes. Model: fixed-effects, Heckman's two-step estimation; dep. var.: ln HHW collected amount by wastecategory: Reclaimable (*ReclCollQ*), Flammable and Poison (*FPCollQ*), Electronic (*EWCollQ*), Acid (*AcidCollQ*), Asbestos (*AsbCollQ*), Base (*BaseCollQ*), Oxidizer (*OxCollQ*), 333 obs. Base case *$RUCC_1$* omitted; estimates for PCB, Universal Waste omitted due to poor model fit. Instrumental var. for *3YCum#PubEdu*: *#CCNewsCA*. Coef. with $p < 0.10$ are highlighted in gray; coef. with $p < 0.05$ bold and italics. Estimated with sampleSelection in R (Toomet and Henningsen, 2008). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

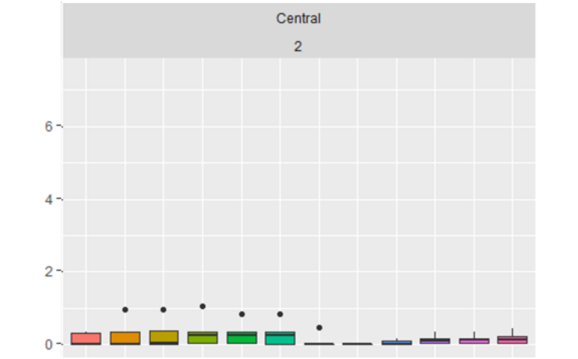
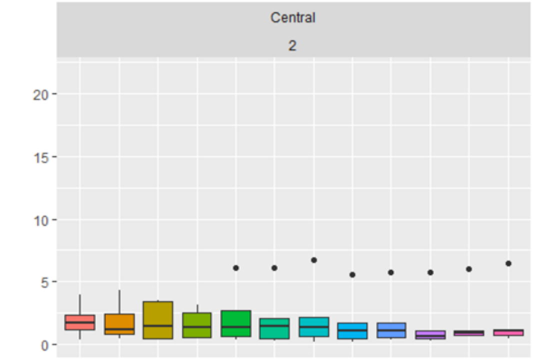
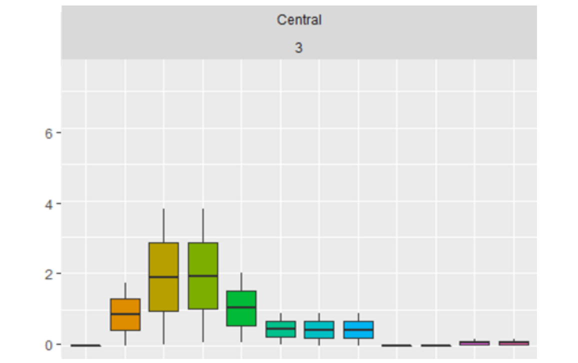
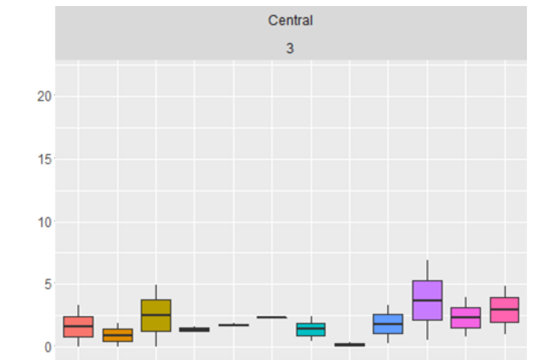
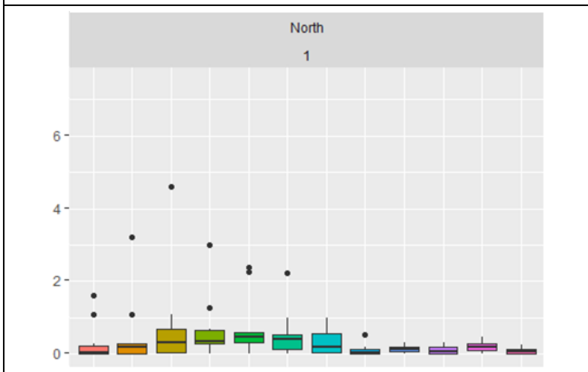
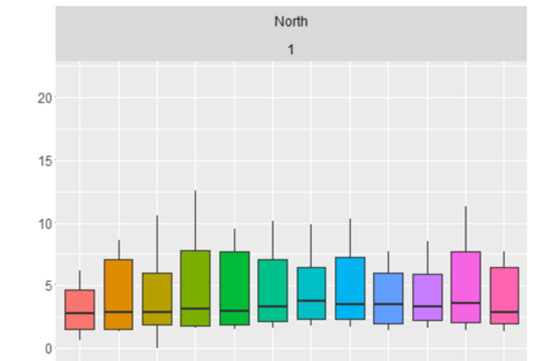
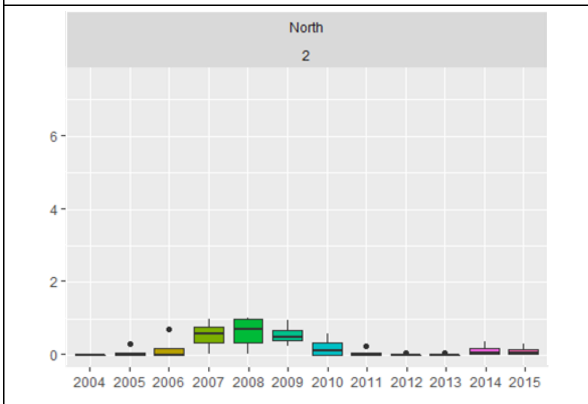
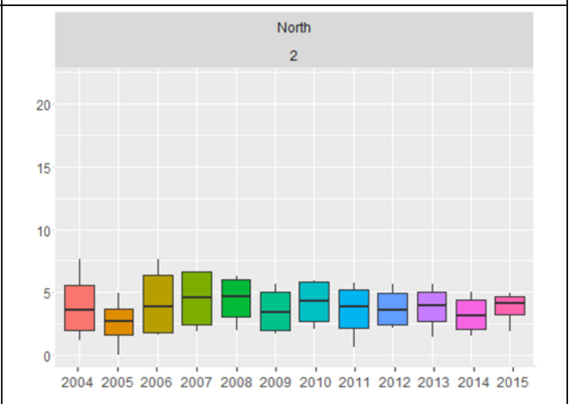
Table D3. Fixed-Effects Model with Heckman Estimation Results Stratified by Material Categories: Probit Analysis

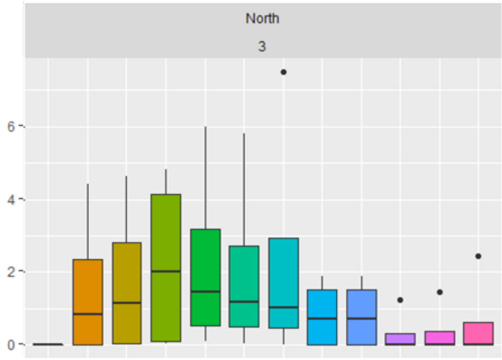
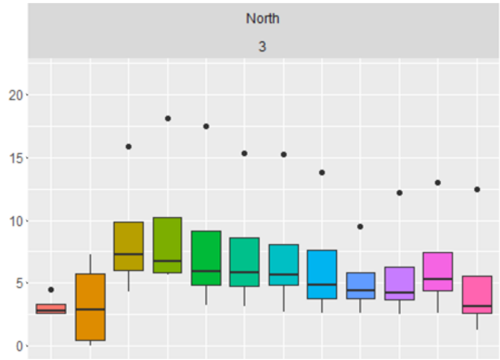
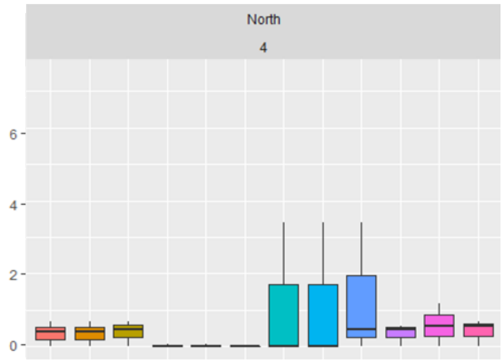
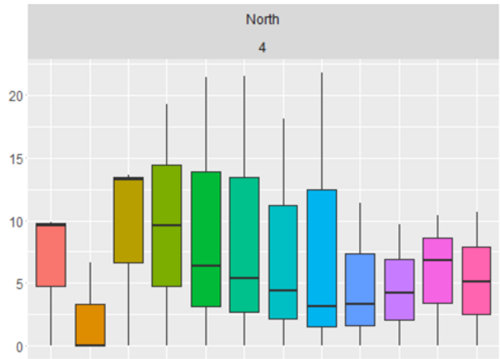
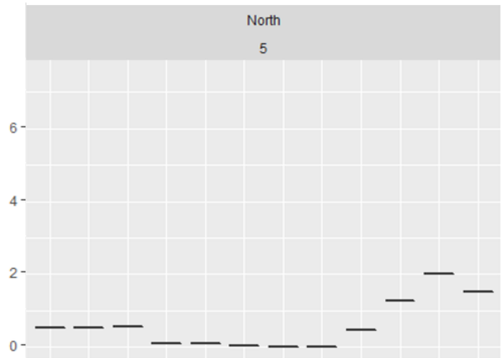
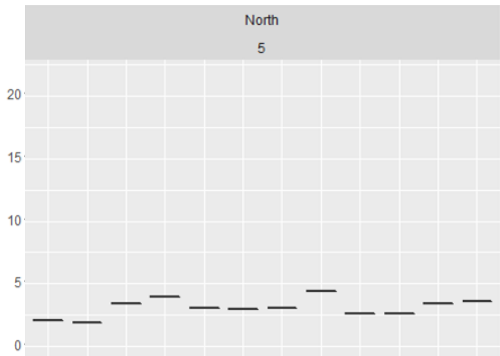
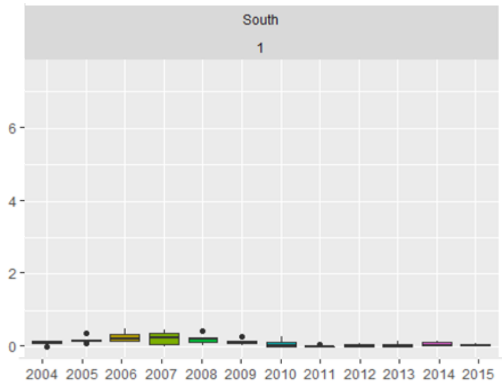
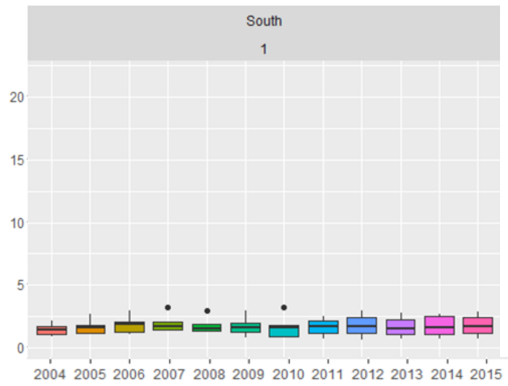
MATERIALS	RECLAIMABLES	FLAMM. & POISON	ACIDS	BASES	OXIDIZER	ASBESTOS
VARIABLES	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Intercept	-39.07 (353.78)	-31.10 (37.45)	-30.22 (18.94)	***-24.58**** (10.23)	***-50.25***** (16.75)	***-25.60***** (3.94)
DHHW Grant	—	—	—	**0.82*** (0.44)	0.60 (0.41)	***0.32**** (0.16)
EduHS%	-7.71 (9.10)	-7.81 (9.60)	-2.33 (2.63)	0.95 (1.72)	0.94 (1.70)	1.53 (1.05)
ln(*MeanHH Income*)	3.81 (3.53)	3.67 (3.40)	**3.12*** (1.76)	***2.30**** (0.96)	***4.64***** (1.55)	***2.19***** (0.38)
# censored	1	1	3	11	11	128
# observed	332	332	330	322	322	205
χ^2	5.40	4.41	***7.87****	***15.90*****	***25.60*****	***64.35*****
McFadden R^2	39.7%	22.0%	23.0%	16.5%	26.5%	14.5%

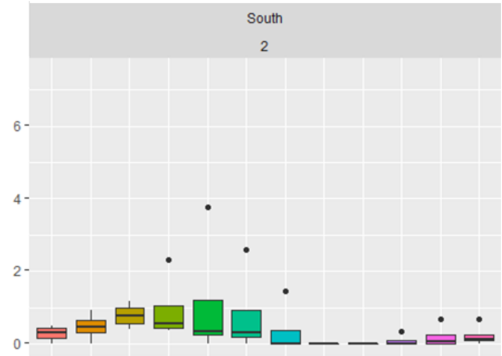
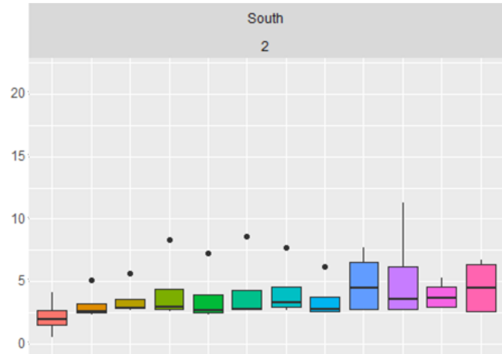
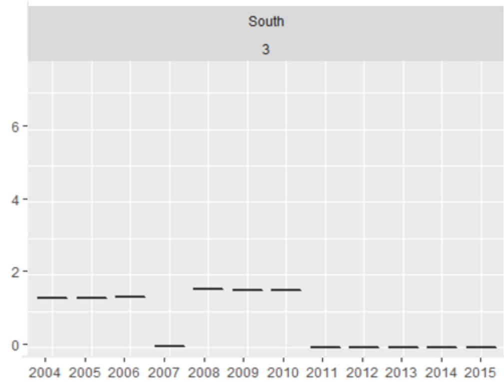
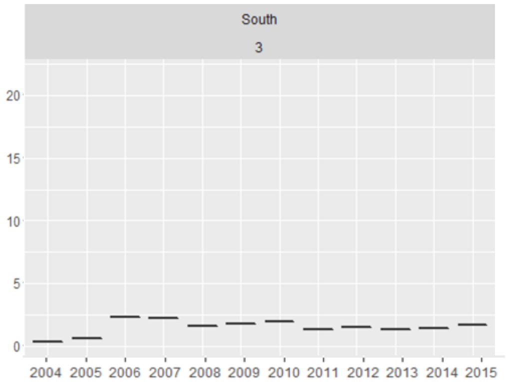
Notes. Model: probit; dep. var.: binary variable to indicate HHW material collected for each waste material category: Reclaimable (*DReclCollQ*), Flammable/Poison (*DFPCollQ*), Acid(*DAcidCollQ*), Asbestos (*DAsbCollQ*), Base (*DBaseCollQ*), and Oxidizer (*DOxCollQ*); 333 obs. Estimates for Electronic, PCB-containing, and Universal Waste omitted due to poor model fit. Coef. with $p < 0.10$ highlighted in gray; coef. with $p < 0.05$ in bold and italics. Estimated with sampleSelection in R (Toomet and Henningsen, 2008). Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendices for Chapter 3

APPENDIX A. BOXPLOTS OF HHW GRANTS VS. COLLECTION DENSITY

3-YEAR CUMULATIVE HHW GRANT ($ PER PERSON)	HHW COLLECTION DENSITY (POUNDS PER PERSON)
	
	
	
	

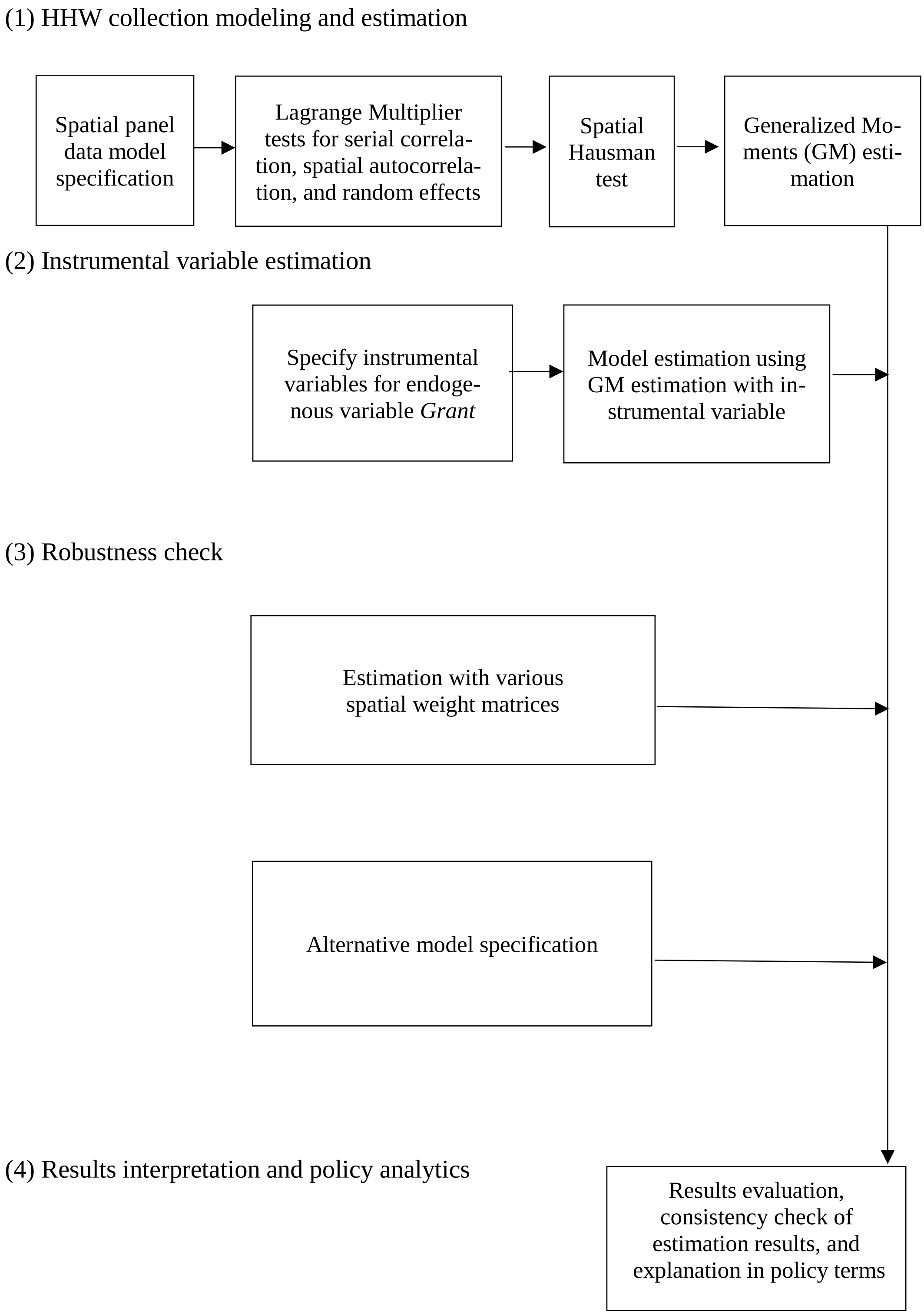
3-YEAR CUMULATIVE HHW GRANT ($ PER PERSON)	HHW COLLECTION DENSITY (POUNDS PER PERSON)
	
	
	
	

3-YEAR CUMULATIVE HHW GRANT ($ PER PERSON)	HHW COLLECTION DENSITY (POUNDS PER PERSON)
	
	

Notes. The boxplots on the left are the 3-year cumulative HHW grant and the ones on the right are HHW collection density. All are by region and the rural-urban continuum codes: 1 – counties in metro areas of 1 million population or more, 2 – counties in metro areas of 250,000 to 1 million population, 3 – counties in metro areas of fewer than 250,000 population, 4 – urban population of 20,000 or more and adjacent to a metro area, 5 – urban population of 20,000 or more and not adjacent to a metro area.

APPENDIX B. MODELING AND ESTIMATION

Figure B1. Research Methods Roadmap



APPENDIX C. ROBUSTNESS CHECK

Table C1. Spatial panel data model estimation results with different spatial weights

VARIABLES	SPATIAL RANDOM EFFECTS WITH 25 NEAREST NEIGHBORS			SPATIAL RANDOM EFFECTS WITH 35 NEAREST NEIGHBORS		
	COEF.	SE		COEF.	SE	
3YcumGrant$ γ	1.19	0.52	**	1.20	0.54	**
λ	0.70	0.25	***	0.64	0.28	**
α	-34.48	13.58	**	-35.10	14.17	**
EduHS% β_1	8.26	4.05	**	10.45	3.98	***
ln (*HHInc*) β_2	2.88	1.32	**	2.81	1.39	**
ln (*Density*) β_3	-0.71	0.34	**	-0.75	0.34	**
Pseudo-R^2	92.1%			92.6%		
$Corr^2$	28.4%			29.5%		
SSE	462.5			433.9		

Notes. Baseline model: random-effects; dep. var.: *ColD*; 468 obs. (39 county x 12 years). Instrumental var. for *Cum3YGrant*: *D_CalRecycle* and ln *(TaxSales$)*. The spatial weights were calculated using an adaptive bi-square distance function with 25 and 35 nearest neighbors. The pseudo-R^2 was calculated using the following formula: 1 – (variance of model residuals / variance of HHW collection density). The *$Corr^2$* was calculated using the square of correlation between HHW collection density predicted by the model and the empirical HHW collection density from the data. The difference between the *pseudo-R^2* and *$Corr^2$* indicates how much of the variation is explained by the fixed or random effects (Elhorst, 2014). Spatial error components are not considered in this estimate. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendices for Chapter 4

Abbreviations

CC	Combined cycle	LCOE	Levelized cost of electricity
CCS	Carbon capture and storage	MW	Megawatts
CCUS	Carbon capture, utilization, and storage	MSCF	1,000 standard cubic feet
CEPCI	Chemical Engineering Plant Cost Index	MWh	Megawatt hours
CPP	Clean Power Plan	MWh-g	Megawatt hours-gross (all power output)
CPS	Carbon Pollution Standards	MWh-net	Megawatt hours-net (less parasitic losses)
CPS + R	Carbon Pollution Standards with CCS retrofit	NETL	National Energy Technology Laboratory
CPS + RW	Carbon Pollution Standards with CCS retrofit and water withdrawal constraint	NREL	National Renewable Energy Laboratory
CT	Combustion turbine	NG	Natural gas
EFOR	Effective forced outage rate	NGCC	Natural gas combined cycle
EGU	Electric generating unit	NSPS	New Source Performance Standard
EIA	Energy Information Administration	OG steam	Oil and gas steam
ELCC	Effective load carrying capacity	O&M	Operations & management
EOR	Enhanced oil recovery	PC	Pulverized coal
EPA	Environmental Protection Agency	PV	Photovoltaic
ERCOT	Electric Reliability Council of Texas	ReEDS	Regional Energy Deployment System
GJ/h	Gigajoules per hour	SC PC	Supercritical pulverized coal-fired
GW	Gigawatts	ST	Steam turbine
IECM	Integrated Environmental Control Model	TSD	Technical support document
IGCC	Integrated gasification combined cycle	USDM	United States Drought Monitor
IPM	Integrated Planning Model	WACC	Weighted average cost of capital
kW	Kilowatts	USDM	United States Drought Monitor
kWh	Kilowatt hours	USGS	United States Geological Survey

APPENDIX A. MASS-BASED CO_2 ALLOWANCE ALLOCATIONS

Table A1. CO2 Allowance Allocations for ERCOT's Affected Existing Generating Technologies

Existing Technologies	CO_2 Allowances (short tons)	Existing Technologies	CO_2 Allowances (short tons)
Coal once-through	38,756,913	NGCC once-through	4,834,009
Coal recirc	25,730,841	NGCC recirc	55,664,151
OG steam once-through	3,966,625	NGCC hybrid	1,308,726
OG steam recirc	641,788	NGCC dry	2,001,804

Notes. CO_2 allowances from Allowance Allocation Proposed Rule TSD (U.S. EPA, 2015g)., for affected existing plants in ERCOT's region are listed by technology type and cooling system.

APPENDIX B. COST AND PERFORMANCE METRICS FOR ELECTRIC POWER PLANT TECHNOLOGIES

Table B1. New Plants: Cost and Performance Metrics

Technology	Var O&M ($/MWh)	Fixed O&M ($/kWYr)	Capital Cost ($/kW)	Heat Rate (MMBtu/ MWh)	Plant Size (MW)	CO_2 Emission Rate (Short Ton/ MMBtu)	Water Withdrawal Rate (gal/MMBtu)	Water Consump-tion Rate (gal/MMBtu)	ELCC
Nuclear recirc	2.14	93.28	5.530	10.4	1,117	0.000	105.9	64.6	0.96
Nuclear hybrid	2.14	93.28	5,761	10.4	1,117	0.000	60.5	36.9	0.96
Nuclear dry	2.14	93.28	6,020	10.4	1,117	0.000	15.1	9.2	0.96
Coal recirc	5.61	66.02	2,252	8.7	550	0.102	67.0	56.8	0.93
Coal hybrid	4.44	69.02	2,521	9.0	550	0.103	38.3	32.4	0.93
Coal dry	4.63	68.32	2,374	9.0	550	0.103	9.5	8.1	0.93
Coal CCS recirc	9.71	107.63	3,972	12.0	550	0.010	91.5	70.5	0.93
Coal CCS hybrid	13.75	110.38	4,257	12.3	550	0.010	75.5	58.2	0.93
Coal CCS dry	12.55	108.41	3,994	12.3	550	0.010	59.5	45.8	0.93
IGCC	8.25	89.66	2,787	8.5	622	0.099	49.9	44.8	0.93
IGCC CCS	10.79	122.36	3,970	10.8	517	0.010	61.3	50.9	0.93
NGCC recirc	3.27	15.37	1,023	6.4	400	0.059	38.0	31.9	1.00
NGCC hybrid	3.27	15.37	1,115	6.4	400	0.059	19.4	16.3	1.00
NGCC dry	3.27	15.37	1,235	6.4	400	0.059	0.9	0.3	1.00
Gas CT	10.37	7.04	676	9.8	210	0.059	0.0	0.0	0.95
Wind	0.00	39.55	2,213	1.0	100	0.000	0.0	0.0	0.24
Solar PV	0.00	27.75	4,183	1.0	20	0.000	0.0	0.0	0.60
Coal CCS 20% recirc	6.31	77.18	2,668	9.5	550	0.082	79.1	66.5	0.93
Coal CCS 20% hybrid	7.44	80.25	2.930	9.7	550	0.083	45.2	38.0	0.93
Coal CCS 20% dry	6.46	78.82	2.749	9.7	550	0.083	11.3	9.5	0.93

Notes. Costs, heat rates, plant sizes, and CO_2 emission rates were mostly sourced from U.S. EIA (2013) for nuclear, gas CT, wind, and solar PV; and NETL (2013) for coal, IGCC, and NGCC with/without CCS. Water withdrawal and consumption rates of nuclear, PC, and NGCC plants with once-through and recirculating cooling, and NGCC plants with dry cooling are adopted from Macknick et al. (2012a); for others, the rates were estimated using the correction factor on water withdrawal rates as in Webster et al. (2013). The ELCCs for nuclear, coal, IGCC, NGCC, and gas CT are assumed as in Webster et al. (2013); the ELCC of wind was adopted from ECCO International (2013); and ELCC of solar was based on Perez et al. (2016). The capital cost and water withdrawal rate for generation technologies with hybrid and dry cooling were calculated for the relevant correction factors using IECM (2015). The same is true for fixed and variable O&M costs for coal, OG steam, and NGCC with hybrid and dry cooling.

Table B2. Existing Plants: Cost and Performance Metrics

Technology	Var O&M ($/MWh)	Fixed O&M ($/kWYr)	Heat Rate (MMBtu/ MWh)	Plant Size (MW)	CO_2 Emission Rate (Short Ton /MBtu)	Water Withdraw Rate (Gal /MMBtu)	Water Consump-tion Rate (Gal /MMBtu)	ELCC
Coal once-through	4.48	61.56	11.1	550	0.100	2,600.4	11.9	0.93
Coal recirc	5.73	66.02	11.2	550	0.100	67.0	56.8	0.93
OG steam once-through	0.62	3.16	12.0	210	0.058	0.0	15.2	1.00
OG steam recirc	0.80	3.33	12.2	210	0.058	0.0	15.2	1.00
NGCC once-through	0.00	13.54	7.8	400	0.061	1,674.0	15.2	1.00
NGCC recirc	3.27	15.37	7.8	400	0.061	38.0	31.9	1.00
NGCC hybrid	3.20	17.05	7.8	400	0.061	19.4	16.3	1.00
NGCC dry	3.21	16.83	7.8	400	0.061	0.0	0.0	1.00
Wind	0.00	39.55	1.0	100	0.000	0.0	0.0	0.24
Solar PV	0.00	27.75	1.0	20	0.000	0.0	0.0	0.60
Nuclear once-through	2.14	93.28	10.4	1,117	0.000	4,264.4	25.9	0.96
Nuclear recirc	2.14	93.28	10.4	1,117	0.000	105.9	64.6	0.96
Gas CT	10.37	7.04	12.6	210	0.063	0.0	0.0	0.95
Hydroelectric	0.00	14.13	1.0	500	0.000	4,491.0	4,491.0	0.96

Notes. Sources: U.S. EIA (2013a), NETL (Black, 2013), Webster et al. (2013), Macknick et al. (2012a). water withdrawal rates for plants with hybrid and dry cooling are calculated using correction factors, as discussed earlier. Variable and fixed O&M costs for coal, OG steam, and NGCC with hybrid and dry cooling were adjusted using correction factors calculated from IECM estimates. OG steam costs are based on average costs used in IPM v.5.15; and the CO_2 emission and heat rates were calculated based on their average rates at existing plants in the ERCOT region in 2012. Under scenarios that implement CPP, a 2.3% heat rate improvement for existing coal-fired EGUs is applied. So, their average heat rate in ERCOT is expected to decrease from 11.2 MMBtu per MWh to 10.9 MMBtu per MWh, with a retrofit cost of $100 per kW (U.S. EPA, 2014b). Water use in hydroelectric is unique because a huge amount of water flows to spin the turbines so the water withdrawal of hydroelectric was assumed to be the same as its water consumption instead of the volume of water flow.

Table B3. Existing Coal and NGCC with CCS Retrofit: Cost and Performance Metrics

Technology	Var O&M ($/MWh)	Fixed O&M ($/kWyr)	CCS Retrofit Capital Cost ($/kW)	Heat Rate (MMBtu/ MWh)	Plant Size (MW)	CO_2 Emissions (Short Ton/ MMBtu)	Water Withdrawal Rate (Gal/ MMBtu)	Water Consumption Rate (Gal/ MMBtu)	ELCC
Existing coal recirc + CCS	11.29	121.23	1,409	13.8	468	0.010	93.9	72.2	0.93
Existing NGCC recirc + CCS	3.74	40.43	696	9.1	344	0.006	63.3	47.4	1.00
Existing NGCC hybrid + CCS	3.78	44.13	786	9.3	344	0.006	55.0	41.2	1.00
Existing NGCC dry + CCS	3.54	41.04	708	9.1	344	0.006	45.9	34.4	1.00

Notes. Capital costs of CCS retrofit, O&M costs, heat rates, and CO_2 rates are estimated using IECM; water withdrawal and consumption rates follow NETL's estimates (Black, 2013); water withdrawal rate for plants with hybrid and dry cooling is calculated using the correction factors from IECM.

APPENDIX C. COST AND PERFORMANCE COMPARISON BY PLANT TYPE, CCS, AND COOLING SYSTEM USING IECM

Table C1. For a New PC Plant with and without CCS

Super Critical Pulverized Coal	CO2 (ton/ MMBtu)	Water Withdrawal (ton/yr)	Water Consumption (ton/hr)	Capital Cost ($/kW-Net)	Fixed O&M ($/kW)	Variable O&M ($/MWh)	Plant Heat Rate (MMBtu/ MWh)
With recirc cooling (base)	0.092	9,337,000	6,547,000	2,031	66.64	2.77	8.9
With dry cooling	0.092	1,937,000	973,100	2,141	68.97	2.29	9.3
With hybrid cooling	0.092	–	–	2,273	69.68	2.20	9.3
CCS 20% with recirc cooling	0.074	11,030,000	7,666,000	2,374	79.56	79.56	9.8
CCS 20% with dry cooling	0.074	3,750,000	2,195,000	2,479	79.56	79.56	10.0
CCS, recirc cooling (base)	0.009	–	–	3,544	105.13	9.94	12.4
CCS, dry cooling	0.009	–	–	3,563	105.89	12.85	12.7
CCS, hybrid cooling	0.009	–	–	3,798	107.82	14.08	12.7

Notes. The costs and rates were calculated using IECM. Those of plants with hybrid cooling were estimated based on a comparative study by Zhai and Rubin (2016). A new PC plant is specified as a typical new supercritical pulverized coal plant with traditional air pollution controls. The ambient air temperature was set to the average temperature in Texas from 1901-2015 (NOAA, 2015). The bypass design for partial CO_2 capture and Amine System FG+, a popular approach for CO2 capture, were selected if the plant had a CCS system. The cooling system used was wet or dry. The applicable correction factor is the ratio of the costs or rates of coal with 20% CO_2 capture and without CO_2 capture. Variable O&M costs were calculated without the fuel costs included also.

Table C2. For a New NGCC Plant with and without CCS

New NGCC	Capital Cost ($/kW-Net)	Fixed O&M ($MM/yr)	Variable O&M ($MM/yr)	Net Electrical Output (MW)	Heat Rate (MMBtu/ MWh)
With recirc cooling (base)	772	10.40	196.2	207	6.82
With hybrid cooling	933	11.20	192.0	206	6.92
With dry cooling	824	11.10	192.8	209	6.92
CCS, recirc cooling	1,397	18.21	206.9	207	7.88
CCS, hybrid cooling	1,578	19.22	208.8	206	8.05
CCS, dry cooling	1,472	18.74	209.2	209	8.05

Notes. The costs and rates were calculated using IECM. For plants with hybrid cooling, they were estimated based on a comparative study by Zhai and Rubin (2016). A new NGCC plant was specified as a typical new plant with two GE 7FB gas turbines, and a 75% load capacity factor; natural gas cost was assumed to be $7.476/mscf; and ambient air temperature, CCS and cooling systems were the same as in the specification of a new PC plant in Texas.

Table C3. For Existing PC Plants

Subcritical Pulverized Coal	CCS Retrofit Cost ($/kW-Net)	Fixed O&M ($/kW)	Variable O&M ($/MWh)	Net Electrical Output (MW)	Heat Rate (MMBtu /MWh)
With recirc cooling (base)	0	60.95	2.33	550	9.4
With once-through cooling	0	64.21	2.98	550	9.5
+CCS with recirc cooling	1,409	121.23	11.29	468	13.8

Notes. Costs and rates for coal wet-once-through and coal wet-recirculating were calculated using IECM. Existing PC plants were specified as fully-amortized subcritical pulverized coal plants. The coal type, capacity factor, ambient air temperature, CCS system, and cooling system were specified as in IECM for a new PC plant. Variable O&M cost does not include the fuel cost component. A retrofit factor of 1.25 for CCS retrofit costs is applied for integrating CCS systems into plants.

Table C4. For Existing NGCC Plants

Existing NGCC	Retrofit Cost ($/kW-Net)	Fixed O&M ($MM/Yr)	Variable O&M ($MM/Yr)	Net Electrical Output (MW)	Heat Rate Net (MMBtu/MWh)
With recirc cooling (base)	0	10.0	189.4	558	7.08
With once-through cooling	0	8.9	188.3	562	7.00
With dry cooling	0	10.6	186.1	543	7.16
+ CCS, recirc cooling	696	19.4	200.1	479	8.20
+ CCS, dry cooling	708	19.4	197.1	473	8.22

Notes. The costs and rates were calculated using IECM using the specification listed above. An existing NGCC plant was specified as a fully amortized NGCC plant with two GE 7FA gas turbines, and a 75% load capacity factor; natural gas cost, ambient air temperature, CCS and cooling systems were the same as in the specification of a new NGCC plant in Texas. As in existing PC plants, a retrofit factor of 1.25 for CCS retrofit costs is applied to integrating CCS systems into plants.

APPENDIX D. CORRECTION FACTORS BY POWER GENERATION TECHNOLOGY

Table D1. Costs and Water Use Correction Factors

TECHNOLOGY	VAR O&M ($/MWH)	FIXED O&M ($/KWYR)	CAPITAL COST ($/KW)	HEAT RATE (MMBTU/ MWH)	WATER WITHDRAWAL RATE (GAL/ MMBTU)	WATER CONSUMP-TION RATE (GAL/ MMBTU)
Nuclear recirc	1.00	1.00	1.00	1.00	1.00	1.00
Nuclear hybrid	1.00	1.00	1.04	1.00	0.57	0.57
Nuclear dry	1.00	1.00	1.09	1.00	0.14	0.14
Coal recirc	1.00	1.00	1.00	1.00	1.00	1.00
Coal hybrid	0.79	1.05	1.12	1.04	0.57	0.57
Coal dry	0.83	1.03	1.05	1.04	0.14	0.14
Coal CCS recirc	1.00	1.00	1.00	1.00	1.00	1.00
Coal CCS hybrid	1.42	1.03	1.07	1.02	0.83	0.83
Coal CCS dry	1.29	1.01	1.01	1.02	0.65	0.65
Coal CCS 20% wet-recirc	1.28	1.17	1.18	1.10	1.18	1.17
Coal CCS 20% hybrid	1.11	1.04	1.10	1.02	0.67	0.67
Coal CCS 20% dry	1.01	1.02	1.03	1.02	0.34	0.29
NGCC recirc	1.00	1.00	1.00	1.00	1.00	1.00
NGCC hybrid	0.98	1.01	1.21	1.11	0.51	0.51
Existing coal recirc	1.00	1.00	–	1.00	1.00	1.00
Existing coal once-through	0.78	0.95	–	0.99	–	–
Existing NGCC recirc	1.00	1.00	–	1.00	1.00	1.00
Existing NGCC once-through	0.99	0.88	–	0.99	–	–
Existing NGCC hybrid	0.98	1.01	1.21	1.11	0.51	0.51

Notes. The factors for variable O&M, fixed O&M, capital costs, and heat rate were calculated using results estimated in IECM. The factors for water withdrawal and consumption rates were calculated using the water withdrawal rates estimated in Webster et al. (2013), except for the rates of Coal CCS 20% (using IECM). All technologies with wet cooling (in gray highlight) have a correction factor of 1, indicating the benchmark for calculating the correction factors of the corresponding technologies with wet once-through, hybrid, and dry cooling.

APPENDIX E. THE POWER PLANT CAPACITY EXPANSION OPTIMIZATION MODEL

This appendix provides details of an optimization model that was built to permit carbon pollution and water withdrawal outcomes to be analyzed in terms of the projected parameters for the ERCOT fleet power generation decision variables in an integer program that characterizes choices to be made under four pathway scenarios involving different generation and cooling technologies, CO_2 emission policies, and water withdrawal limitations. For the details of the modeling notation, see Table E1.

Table E1. Modeling Notation in the Integer Programming Formulation

Notation	Definition	Comments
i, j	Subscripts: technology *i*; load strip *j* in a discretized load duration curve	$i \in I$ that includes sets of: 20 new, 2 new renewable with set aside, 14 existing, 4 and existing with CCS retrofit technologies; load duration curve discretize into 20 sequentially-ordered hourly-load strips; $j \in J = \{1, 2, \ldots, 438)$ with 1 = peak load strip
New, RenewSetAside, Retro, Exist	Sets of technologies: new, renewable with set-aside, existing with CCS retrofit, and existing technologies.	
$Number_i$	Number of EGUs of technology *i*	Decision variables for $i \in \{New, RenewSetAside, Retro\}$ but fixed values for $i \in Exist$
$ExistNumber_i$	Number of EGUs of existing technology i	Number of existing EGUs
$Fraction_i$	Fraction of remaining EGUs of technology *i*	Decision variables for $i \in Exist$
Gen_{ij}	Electricity generation (in MWh) of EGUs of technology *i* dispatched to meet the load demand in load strip *j*	Decision variables for electricity generation for technologies
$CO_2AllowBuy_i$, $CO_2AllowSell_i$ $CO_2AllowOutputBased_i$	CO_2 allowance (in short tons) of technology *i* purchased from the market; sold to the market; assigned to existing NGCC plants	Decision variables for CPP-affected existing technologies only: coal, OG steam, and NGCC
$Capacity_i$	Plant nameplate capacity (MW) for an EGU of technology *i*	Intended full-load output of EGU; assumed equal for all EGUs of same technology
$CapRecovFactor_i$	Capital recovery factor (fraction/yr) of technology *i*	Factor for annualized cost of capital
$RetroCostHeat_i$	Retrofit cost ($/kW) to decrease heat rate of technology *i*	Cost to improve energy efficiency of existing technology; only applicable for coal-fired technology in carbon-regulated scenarios; $100 per kW (EPA)
$RetroCostCCS_i$	CCS retrofit cost ($/kW) of technology *i*	Applied to existing coal-fired and NGCC EGUs only
$ServLife_i$	Economic service life (yrs) of technology *i*	30 years for all technologies, except for wind
$HeatRate_i$	Heat rate (in MMBtu/MWh) of technology *i*	Energy input to a system divided by electricity generated
$CO_2CaptureRatio_i$	Percent CO_2 captured relative to the percent that is not, for technology *i*	Ratios are 9:1 for technologies with full CCS; and 1:4 for technologies with 20% capture
$Demand_j$	Demand (MWh) in load strip *j*	Demand is average of hourly load in load strip $j \times 20$ (hourly load instances); first strip uses peak load
$ELCC_i$	Effective load carrying capacity % of technology *i*	Determines maximum load capacity of a plant's technology
$WaterWithRate_i$	Water withdrawal rate (gal/MMBtu) of technology *i*	Amount of water a power plant takes in from the source (e.g.,

Notation	Definition	Comments
		river, lake), some of which is returned, per energy produced
CO_2Allow_i	Allocated CO_2 allowance (short tons) of technology i	Allocation based on historical generation in 2012 for CPP-affected technologies only
$CO_2EmissionRate_i$	CO_2 emission rate (short tons/MMBtu) of technology i	Mass of CO_2 released per unit energy produced
$RenewIncentive_i$	Renewable incentive ($/MWh) of technology i	Assumed to be $2.72/MWh and applicable for new renewable with set-aside only
$InvestCost_i$, *TotInvestCost*	Capital investment cost ($/kWyr) of technology i; total capital investment cost ($)	Cost of building a power plant
$FixCost_i$, *TotFixCost*	Fixed O&M cost ($/kWyr) of technology i; total fixed O&M cost ($)	O&M: operation & maintenance
$VarCost_i$, *TotVarCost*	Variable cost O&M cost (in $/MWh) of technology i; total variable O&M cost ($)	Variable operation & maintenance cost, not including fuel cost
$FuelCost_i$, *TotFuelCost*	Fuel cost ($/MMBtu) of technology i; total fuel cost ($)	Fuel cost varies by technology
$TotCO_2TSCost$	Total CO_2 transport and storage cost	CO_2 transport and storage cost assumed to be $3/short ton and $7/short ton of CO_2 captured
NetCost	Net annual cost of electricity ($)	Total cost of electricity - offsets
$TotCO_2AllowCost$	Total CO_2 emissions allowance purchase cost ($)	# allowances purchased × price
$TotCO_2AllowOffset$	Total CO_2 emissions allowance sale offsets ($)	# allowances sold × price
TotRenewSetAsideOffset	Total offsets from selling renewable set-asides ($)	# allowances sold from renewable set-aside × price
$TotCO_2CaptureOffset$	Offsets from selling captured CO_2 for EOR ($)	CO_2 offsets sold for EOR × price
WACC	Weighted average cost of capital (%)	Discount rate of 7% is used
$CO_2EORPrice$	Sale price of captured CO_2 for enhanced oil recovery ($/short ton)	Sale price = $0/short ton, ref case
Reserve%	Capacity reserved (%) beyond peak demand	Reserve margin of 16.1%
WaterWithLimit	Water withdrawal limit (gallons)	50% of 2012 level (1,900 billion gallons)

The objection function of the expansion model is:

Min *NetCost* = *f* [(*TotCosts*; *TotOffsets*]

$$= f\,[TotInvestCost, TotVarCost, TotFixCost, TotFuelCost, TotCO_2TSCost, TotCO_2AllowCost; TotCO_2CaptureOffset, TotCO_2AllowOffset, TotRenewSetAsideOffset] \quad (1)$$

The total fleet investment cost is the sum of the capital costs of new EGUs, the retrofit costs for improving the heat rate of existing EGUs (if applicable), and the retrofit costs for adding a CCS system to coal and natural gas-fired EGUs (if applicable). These costs are annualized using a *capital recovery factor*:

$$TotInvestCost = \sum_{i\in\{New,RenewSetAside} [Number_i \times Capacity_i \times CapRecovFactor_i + \sum_{i\in Retro} [Number_i \times Capacity_i \times CapRecovFactor_i \times RetroCostCCS_i] + \sum_{i\in Exist} [Fraction_i \times ExistNumber_i \times Capacity_i \times CapRecovFactor_i \times RetroCostHeat_i] \quad (2)$$

where $CapRecovFactor_i = \frac{WACC}{1-\frac{1}{(1+WACC)^{ServLife_i}}}$.

The *weighted average cost of capital*, *WACC*, is assumed at 7%, as in regulatory assessments.

Economic service life for all generation technologies is 30 years, except for wind at 20 years (Webster et al., 2013). All existing EGUs are fully amortized. *Total fixed O&M cost* for new and existing EGUs is estimated via:

$$TotFixCost = \sum_{i \in \{New, RenewSetAside\}} [Number_i \times Capacity_i \times FixCost_i] + \sum_{i \in Exist} [Fraction_i \times Number_i \times Capacity_i \times FixCost_i] \quad (3)$$

Total variable O&M cost and *total variable fuel cost* are estimated for all EGUs based on:

$$TotVarCost = \sum_i \sum_j [Gen_{ij} \times VarCost_i] \quad (4)$$

$$TotFuelCost = \sum_i \sum_j [Gen_{ij} \times HeatRate_i \times FuelCost_i] \quad (5)$$

Revenues from selling renewable set-aside pool allowances are calculated by multiplying the amount of electricity generated by the new set-aside by the incentive rate:

$$TotRenewSetAsideOffset = \sum_{i \in (RenewSetAside\}} \sum_J [Gen_{ij} \times RenewIncentive_{ij}] \quad (6)$$

The U.S. EPA (2015d) estimated the *levelized cost of electricity* (LCOE) for wind power: the cost normalized for advantages and disadvantages of the type and location for energy production. Assuming an allowance rate of $13 per short ton and an incentive of $2.72/MWh, the EPA estimated that the renewable set-aside of 5% of total allowance to be reasonable to mitigate emissions leakage to new NGCC EGUs. So the same incentive rate in the model is included.

The revenue from selling captured CO_2 for EOR operations will decrease the total cost of electricity when this is implemented through the technology in the CCS system, based on the following relation:

$$TotCO_2CaptureOffset = \sum_i \sum_j [Gen_{ij} \times HeatRate_i \times CO_2Emission_i \times CO_2CaptureRatio_i \times CO_2EORPPrice_i] \quad (7)$$

The *CO_2 capture ratio* is the percent captured relative to the percent that is not. Captured CO_2 can be sold at a price that is established in the market. Note that the *CO_2EmissionRate* in this equation accounts for the rate with carbon capture for EGUs with CCS.

In addition, when a CO_2 emission allowance trading program is available, the *allowance purchase cost* (*CO_2AllowCost*) is the cost that an EGU faces to acquire a *CO_2 emission allowance* (*CO_2AllowBuy*) from the market. An EGU can also gain some *allowance selling revenue* (*CO_2AllowOffset*) if it sells *its excess allowances* (*CO_2AllowSell*) to the market for other EGUs to buy. An *allowance rate* (*AllowRate*) of $13 per short ton is assumed in this model (U.S. EPA (2015d).

The constraints in the model include:

- **Electricity demand and balance. (1 constraint).** Electricity generated must be equal to electricity demanded in each load strip:

  $$\sum_i \sum_j [Gen_{ij}] = Demand_j, \ \forall j \quad (8)$$

- **Load capacity for minimum and maximum electricity generation (5 constraints).** The different technology types may have different minimum and maximum load capacity. Coal-fired EGUs must have a capacity factor equal to or 50% greater in each period. All plants will have maximum load capacities that are determined by their *effective load carrying capacity* (*ELCC*). Existing EGUs may retire so the maximum load capacities will be adjusted for only unretired EGUs. The constraints for existing plants with renewable energy resources are all bounded by the *annual capacity factor* defined for 2012. In addition, the 2012 annual capacity factor also is the upper bound for energy from nuclear plants, though availability varies geographically (U.S. EPA, 2013). A sample is:

  $$Gen_{ij} \le ELCC\%_i \times Number_i \times Capacity_i \times 20\ Hours, \forall i, \forall j \quad (9)$$

  Note that we use 20 hours in the above equation because we discretized the one-year load duration curve into 438 load strips of 20 hours each.

- **Reserve electricity generation capacity (1 constraint).** Electricity generating capacity must be greater than or equal to that required by the peak demand, plus some additional reserve capacity:

$\sum_i \ [ELCC_i \times Number_i \times Capacity_i] \geq (1 + Reserve\%\ )[\max_j Demand_j]$ (10)

- **Water withdrawal limit (1 constraint).** When a limit is applicable, water withdrawals over a year must be less than a regulatory cap for a specific power generation technology:

  $\sum_i \sum_j \ [Gen_{ij} \times HeatRate_i \times WaterWithRate_i] \leq WaterWithLim$ (11)

- **Clean Power Plan compliance (7 constraints).** The applicable constraints are for CO_2 emission caps for existing plants, CO_2 allowance trading, renewable set-asides, and output-based (for NGCC plants only) under EPA's CPP rules, so that a plant can emit CO_2 to the extent of its historical allowance, plus any other allowances it buys. If some EGUs are retrofitted with CCS, their CO_2 allowances are divided proportionately to the capacity of EGUs with and without retrofit. The main constraint for allowance trading is:

  $\sum_j \ [Gen_{ij}\times HeatRate_i\times CO_2Emission_i] = (Fraction_i\times CO_2Allow_i) + CO_2AllowBuy_i + CO_2AllowOutputBased_i - CO_2AllowSell_i, for\ i \in \{ExistingCoal, OG\ Steam, NGCC\}$ (12)

  The model also applied an emission cap on the total CO_2 emissions, which is the sum of the state's mass-based goal and new source complements proposed by the EPA.

The six constraints of Eqs. 8 to 10 are *EGU technical constraints* for the operational requirements of a power fleet. The constraints of Eqs. 11 and 12 are *energy policy constraints* on water withdrawal and CO_2 emissions. There are other equations that we suppressed that are *logical constraints* so the math program will produce meaningful solutions. They are: variables for new EGUs should be greater than or equal to 0; the fraction of the number of existing EGUs must range from 0 to 1; other variables should be strictly positive.

APPENDIX F. ELECTRICITY GENERATION SHARE ANALYSIS

Table F1. Share of Electricity Generation by Cooling Technology by Scenarios

Scenarios and Power Tech	Wet-Once-Through	Wet-Recirc	Hybrid	Dry
BAU				
Coal	54.3%	45.7%	0.0%	0.0%
NGCC	19.5%	79.6%	0.2%	0.6%
Nuclear	51.8%	48.2%	0.0%	0.0%
OG steam	100.0%	0.0%	0.0%	0.0%
All sources	40.6%	59.1%	0.1%	0.2%
CPS				
Coal	54.8%	45.2%	0.0%	0.0%
NGCC	16.6%	75.4%	0.4%	7.6%
Nuclear	51.8%	48.2%	0.0%	0.0%
OG steam	100.0%	0.0%	0.0%	0.0%
All sources	33.1%	62.5%	0.2%	4.2%
CPS + R				
Coal	54.8%	45.2%	0.0%	0.0%
NGCC	16.6%	75.4%	0.4%	7.6%
Nuclear	51.8%	48.2%	0.0%	0.0%
OG steam	100.0%	0.0%	0.0%	0.0%
All sources	33.1%	62.5%	0.2%	4.2%
CPS + RW				
Coal	53.8%	46.2%	0.0%	0.0%
NGCC	0.8%	90.6%	0.6%	8.0%
Nuclear	38.9%	61.1%	0.0%	0.0%
OG steam	0.0%	100.0%	0.0%	0.0%
All sources	21.0%	73.9%	0.4%	4.7%

Notes. The shares of electricity generation in the table include only thermoelectric plants (coal, NGCC, nuclear, and OG steam) that require cooling systems.